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TOMATO LEAF DISEASE DETECTION USING INCEPTION V3

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Abstract: Agriculture is one of our society's most critical fields, and it has been since the Middle Ages. Crop diseases are a significant threat to food security, but timely detection is difficult due to a complete lack of facilities in many parts of the world. Bacteria and fungi infect tomato plants in several ways. Early blight and late blight are two fungal diseases that affect plants. Bacterial spot is caused by four Xanthomonas species and can be found wherever tomatoes are grown. Smartphone-assisted disease detection is now possible thanks to rising global smartphone penetration and recent developments in machine vision made possible by deep learning. To distinguish different tomato leaves, we trained deep convolutional neural network diseases using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions and choosing the images of tomatoes. Training deep learning models on increasingly broad and publicly accessible image datasets points to a direct path toward global crop disease diagnosis aided by technology.

Keywords: Early Blight, Late Blight, Bacterial spot, Leaf Mold, Septoria Leaf spot, Target Spot, Yellow Leaf Curl Virus, Mosiac Virus, Two Spotted Spider Mite

1. Introduction

Agriculture is one of the fundamental building blocks of every civilization. Growing vegetables like tomatoes are effective in India's diverse range of subtropical climates. A diseased plant has been hindered from achieving its normal state. A disease may also be described as interfering with a plant's yield and reducing its vitality. In India, diseases change with the seasons and are affected by environmental factors. Pathogens and the variety of crops grown during the season play a role in these diseases. Late Blight and Early Blight are two common tomato diseases [1]. They have the potential to damage tomato plants and agricultural lands. Spotting Late Blight and Early Blight on plant leaves is possible, but it takes a long time if performed manually. As a result, more recent changes are needed. With the aid of image processing and computer vision, there are many ways to detect objects and their unique features from images. The deep learning CNN model [2] is one of the most common approaches. The model, in our case, will detect disease based on the picture of the leaves.

Convolutional neural networks are image processing methods using jpg files to comprehend them [3]. Shift invariant is another name for them. Because of their weight-sharing architecture and translation invariance properties, this is the case. As a result, they've also been known as space-invariant neural networks. They're used in recommender systems, image and video recognition, medical image analysis, image detection, natural language processing (NLP) [4], brain-computer interfaces, and financial time series, among other items. They also rule a slew of different applications in a variety of fields. The paper is further classified into sections that discuss various viewpoints in analyzing tomato diseases' impact on Indian agriculture. Raw Dataset was used, and the detail extraction is discussed in section 3.1. The results, the accuracy, and their evaluation have been documented in section 4. The paper is finally concluded on a note with an evaluated conclusion and expectations of future scope in sections 5 and 6, respectively.

2. Related Work

The use of computer vision to identify agricultural diseases has become a hot subject. In the early years, traditional machine learning methods and external networks were commonly used in the agricultural sector. Sannakki et al. [2] proposed using k-means-dependent clustering performed on each image pixel to isolate the infected location. Those who realized that the Grading System they created with machine vision and fuzzy logic is very useful in evaluating plant disease. Samanta et al. introduced a new histogram-based approach for detecting potato scab diseases, which relied on a color image segmentation technique to detect precise intensity patterns. With a classification accuracy of 97.5 percent, they came out on top. Pedro et al. used fuzzy decision-making and a fuzzy multicriteria decision-making approach to classify marijuana form, with an accuracy of 92.9 percent. Matson and Cheng used Support Vector Machine (SVM), Decision Tree, and Neural Network to classify rice and weed, with Decision Tree providing the highest accuracy of 98.2 percent. Sankaran and Ehsani used quadratic discriminant analysis (QDA) and k-nearest neighbor (kNN) to distinguish Huanglongbing (HLB)-infected citrus leaves and canker from healthy citrus leaves, with kNN providing overall accuracy of 99.9%. D. Tiwari et al. [3] used transfer learning and various pre-trained models and concluded that VGG 19 provided the best accuracy on the potato leaves image dataset. Backpropagation neural networks have a 92 percent accuracy rate, while support vector machines have a 95 percent accuracy rate. In their research, Melike Sardogan et al. [5] attempted to detect and classify tomato leaf diseases using a Convolutional Neural Network with a Learning Vector Quantization algorithm.

A. Pranathi et al. [6] proposed a small convolutional neural network model variant. To detect and diagnose illnesses in tomato leaves, researchers presented LeNet. Their planned research aims to develop a solution to the challenge of detecting tomato leaf disease using the basic strategy while employing the fewest computational power possible to produce results comparable to the best technologies available. Chittaragi et al. [6] suggested the use of automatic feature extraction in neural network models to assist in the classification of input images into disease classes. Their proposed solution attained an average accuracy of 94 - 95 percent, demonstrating the neural network approach's feasibility even under adverse conditions. U. Mokhtar et al. [7] proposed a method that uses the Gabor wavelet transform approach to extract essential elements from a tomato leaf image, as well as Support Vector Machines (SVMs) [8] with different kernel functions, to discover and diagnose the disease that affects tomato plants. They used actual samples of damaged tomato plants, isolated each leaf in a separate image, and used a wavelet-based feature approach to find the best feature subset. H. Hefny et al. [6] used a support vector machine classifier with several kernel functions such as Cauchy kernel [9], Invmult Kernel, and Laplacian Kernel to test the efficacy of this methodology to detect and identify where tomato leaves infected with Powdery mildew or early blight. Extensive testing shows that the proposed method gives good annotation with a 99.5 percent accuracy rate. The proposed approach's efficient results can lead to a tighter relationship between agriculture specialists and computer systems, resulting in more effective and dependable results.

3. Materials and Methods

This paper aims to use deep learning to detect tomato leaf diseases. Deep neural networks train the model to detect presence after acquiring features from inception v3 [7]. In the photos, you can see early blight and late blight. The Adam optimizer is used during classification to minimize training time and easily converge the loss [10]. Adam is a computer vision extension of SGD [11] that is now commonly used. The softmax activation mechanism is used to classify various labels [10]. The softmax activation function transforms a vector of n real values into a vector of n real values that add up to 1. The softmax [12] converts the input values into values between 0 and 1, allowing them to be interpreted as probabilities.

3.1 Raw Dataset

A dataset is the first step in writing a deep-learning document. It can be used to research and infer even more findings from the model and train it. The data set used in this project is from the Kaggle platform. The data set is named PlantVillage [13], a popular dataset in the Kaggle platform. Kaggle is an online platform for data scientists and machine learning engineers where they can compete in ML competitions and work on various datasets and notebooks. There are approximately 20000 photos of leaves from tomato plants, bell pepper plants, potato plants, and other plants in this Dataset. The images in the Dataset are in jpg/png format. This is a collection of data leaves that are both healthy and diseased. The diseased leaves are divided into early blight and late blight. For stable leaves, 80% of the Dataset is used for preparation, and the remaining 20% is used for testing; the same is true for diseased leaves. As a result, the model will be trained on more leaves and checked on fewer to achieve the highest accuracy during prediction and detection. Each plant has its directory, and each disease associated with that plant has its folder. The Tomato plant dataset is the subset of the Dataset we're working with. There are 1000 images of early blight leaf images, 1000 images of late blight leaf images, and 152 images of late blight leaf images in this Dataset.

Fig. 1 Sample images of the Dataset

3.2 Data Preprocessing

Since the data is in image format, to make it useful for the system to run, we first convert it into an image array with the help of Keras functions. Classification of diseases will only be performed appropriately if the image is colorful so that the model can differentiate between various conditions. So a 3D NumPy [14] array will be generated using RGB values.

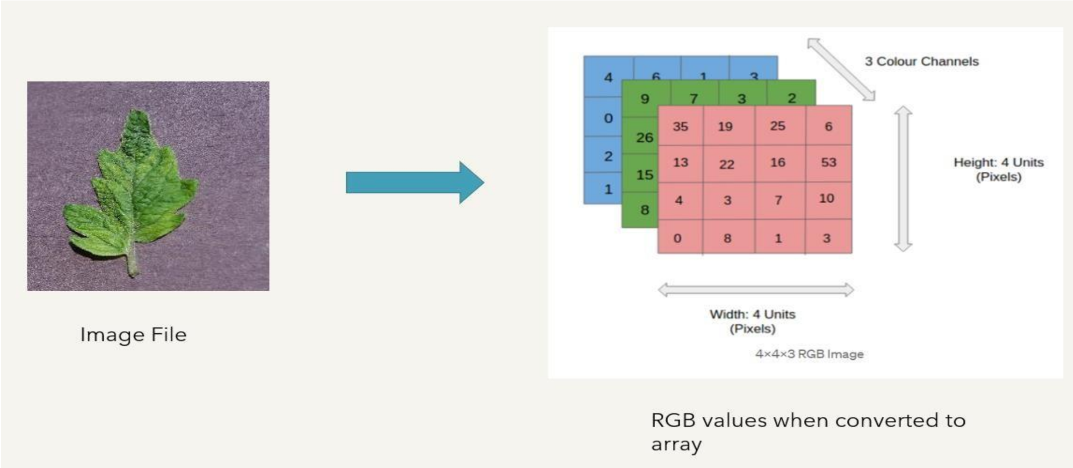

Fig. 2 Converting images to Numpy array

The Inception V3 model derives the learning algorithm from the ImageNet Dataset and uses that learning algorithm in the PlantVillage dataset. ImageNet is already a popularly known labeled image dataset of 14 million labeled images. So to improve the learning algorithm in our Dataset, we will provide labels to our data. After converting the images to arrays, we need to label the data so that the model will classify them in order of classes. Label Binarizer library is used so that the images will be properly labeled into categories with the names of the disease. LabelBinarizer will help classify the data during the training of data.

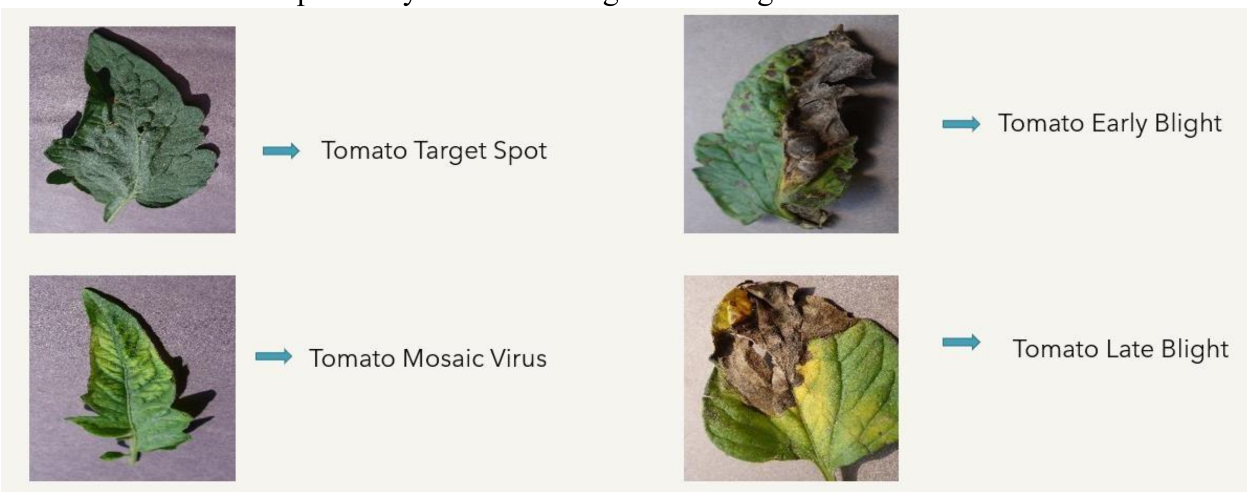

Fig. 3 Labeling Data

3.3 Data Augmentation

We have used CNN to perform classification in this research project. Deep neural networks train the model to detect the existence of early and late blight in the images after acquiring features from Inception v3. Further, we use Adam optimizer during classification to minimize training time and quickly stabilize the loss. Adam[9] is a machine vision extension of SGD [11] that is commonly used. The softmax activation function is used for the classification of different labels. The softmax activation function translates a vector of n absolute values into a vector of n actual values that add up to one. And although input values can be any number, the softmax converts them to a number between 0 and 1, allowing them to be used.

3.4 Deep Learning Models

All images are fed into the CNN model's input layer at the start. The images are then provided in the inception v3 architecture [8] for feature extraction. There are Deep neural nets that identify the images based on pre-trained information using feature-extracted images. The

images are finally sent to the output layer. The model comprises a few layers that are first generated and then compiled together using TensorFlow library functions [8].

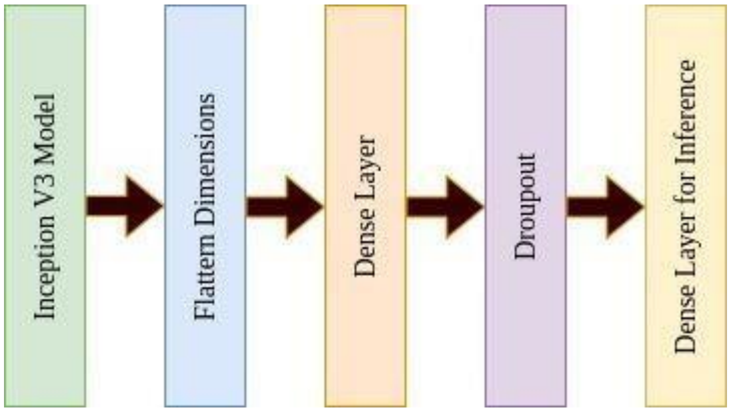

Fig. 4 Abstract form of Inception V3 model

4. Experimental Results and Discussions

The plant village dataset, which contains around 1000 leaf images of early blight and 152 images of healthy plants, was used to develop the model proposed in this paper. The Dataset for this model has been divided into two parts: the training set and the test set. The training set accounts for 80% of the Dataset, while the test set accounts for 20% of the total. Inception V3 is the pre-trained model used to extract features from this Dataset. Based on the training and testing performed, our CNN model offers an accuracy of about 84% for classification, which can be further improved if we are provided with resources to run ML models. Our data set's input images are 128 x 128 pixels, each with RGB colors with a density of 512. This accounts for the shape of our image to be a 3dimensional matrix of 128 x 128 x 3. We use Label Binarizer for providing labels to the input image data. Label Binarizer library is used so that the images will be properly labeled into classes with the names of the disease. Performing an image prediction will result in an output of a 3D NumPy [14] array, which provides an image value. Classification of diseases will only be performed appropriately if the image is colorful so that the model can differentiate between various diseases. So a 3D NumPy [14] array will be generated using RGB values.

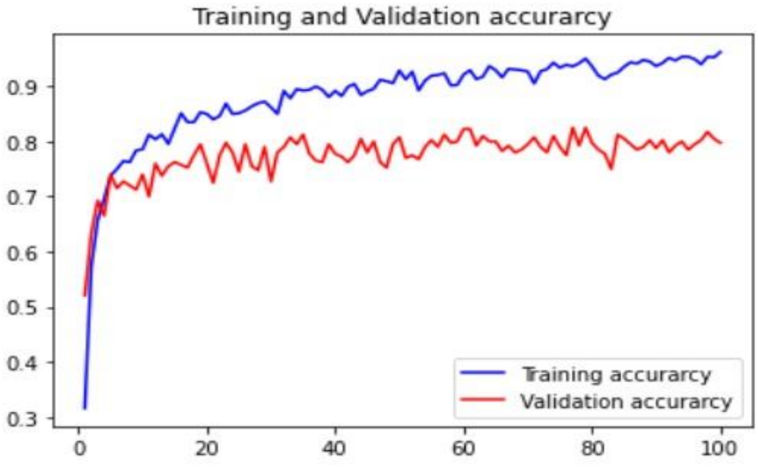

Fig. 5 Training and Validation Accuracy

With an epoch of 70, the training accuracy increases to greater than 90%. However, the validation accuracy (training accuracy subtracted loss) achieves a plateau at ~80 to 85%. With close analysis and evaluation of the model, we get a mean accuracy of 84%.

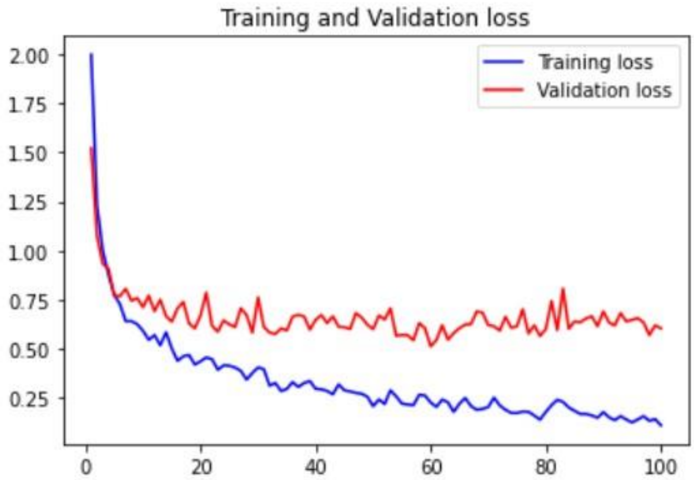

Fig. 6 Training and Validation Loss

With the iteration of every epoch, the model improves the learning method and minimizes the losses. We see an exponential fall in training loss with a conclusion training loss percentage of 10 to 15%. After evaluating the model, we find this mean decrease to 12%. As the training loss (referred to as val_loss) starts decreasing, the training accuracy (referred to as val_acc) increases. This inversely proportional relationship confirms that our model is learning and working as expected.

5. Conclusion

In this study, we used the Inception V3 architecture and Adam Optimiser [15] to create a CNN model to diagnose and identify diseases in tomato plants, such as early and late blight, with a classification accuracy of 90% over the test dataset. With the aid of our model, a farmer can construct a computer setup from which he can effectively track plant health issues, increase crop yield, and detect and diagnose diseases at an early stage.

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CURRENCY RECOGNITION SYSTEM FOR VISUALLY IMPAIRED USING A NOVEL CNN-LSTM BASED HYBRID APPROACH

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Abstract- One of the main problems faced by visually impaired people is dealing with monetary transactions, due to their inability to recognize the value of currency notes because of the identical dimensions and it's feel. We introduce in this paper, a camera phone-based money recognition system that executes real-time processing for every detected frame as the camera advances towards the note using CNN-LSTM algorithm and then generates a corresponding audio message telling about the value of the currency note. To make the system reliable in real-life scenarios, we have created a Currency recognition system (CRS) built on Convolutional neural network (CNN) and Long short-term memory (LSTM). The hybrid CNN-LSTM algorithm obtains results as fast and robust as possible.

Keywords: Currency Recognition, CNN, LSTM, Currency Recognition System (CRS), Indian Currency Detection, CNN-LSTM Hybrid

1. Introduction

According to the latest stats of the World Health Organization (WHO) around 286 million people in the world are visually impaired and about 62 million people are from India. Therefore, to resolve this issue faced by visually challenged people, we propose a visually impaired mobile phone- based money scanner that conducts real-time operation for every recorded frame recorded as the photographic equipment travels towards the note, and then generates a corresponding audio message telling about the value of the currency note to the person. To resolve the issue faced by visually challenged people while detecting the value of the currency, we proposed a mobile phone- based currency reader that conducts real-time processing for each recorded frame as the camera travels towards the note, and then generates a corresponding audio message telling about the value of the currency note to the person. This is done with help of a CNN-LSTM based Hybrid Approach. CNNs are used to model problems involving spatial inputs such as images. For picture-related activities such as computer vision, picture identification, and object detection, CNNs have proven useful. Convolution is the initial level to generate characteristics of a picture. By learning visual characteristics from tiny input data squares, convolution maintains pixel relationships. Two intakes are required for the mathematical procedure to proceed, one of which is an image matrix and the other of which is a filter or kernel. LSTMs are used to model and predict sequences. LSTMs are extensively used in natural language processing tasks like machine translation, sentence classification, and production. The addition of a gating mechanism is a significant advantage of using LSTM over a standard RNN. This gating mechanism consists of an input gate, an output gate, and a forget gate. It is used to regulate the transmission of information between neural networks. In this paper we described how CNN and LSTM technology can be used as a currency recognition system for visually impaired people. So, we introduced a camera phone based model, through which people can recognize a currency note with the camera of their phone. We studied almost 30 research papers in which we covered various techniques and the challenges which earlier authors faced, and we tried to overcome that and develop a robust and sustainable solution. We prepared a model using CNN-LSTM hybrid approach which includes convolutional, pooling and LSTM layers. We used technologies like cloud model deployment, crash detection system and enhanced the camera scanning functionalities which works well even in low light and we used TTS (Text to Speech) technology which helps us convert text to an audio message. After combining all these technologies we prepared a software solution which is robust, sustainable, compatible and works effectively in real life environment showing an accuracy of 92.55%.

1.1 Problem Statement

Owing to the issue faced by visually challenged people while recognizing the value of currency notes because of the resemblance of the feel and size of different notes, one of the main challenges encountered by visually disabled persons is when performing money transactions. There are 3 main challenges in existing current currency recognition systems (CRS) which are listed below:

- Detecting currency value from partially captured images and under different lighting conditions.
- Lack of fast and accurate methods for robust and quick currency recognition.
- Problem from frequent crashes in current applications because heavy machine learning and deep learning processes are running in mobile devices.

These flaws in the existing systems motivates us to work upon this problem statement. To make the system reliable in real-life scenarios, we have created a Currency recognition system (CRS) on the basis o Convolutional neural network (CNN) and Long short-term memory (LSTM). The hybrid CNN-LSTM algorithm obtains results as fast and robust as possible.

A Currency Recognition System (CRS) must possess three functionalities:
Image preprocessing (Elimination of background details)
Feature Extraction
Classification on basis of underlying algorithm
The primary objectives of this research project are as follows:

- To design a model which can recognize currency notes with limited training sets.
- To minimize the computational time of the proposed Currency Recognition System (CRS).
- To optimize the accuracy of the existing Currency Recognition System (CRS).

To deal with the research challenges and achieve these objectives, we are proposing a novel CNN- LSTM based hybrid approach for Currency Recognition system (CRS) in this research.

2. Background Study

The authors, [1] have incorporated a currency recognition system (CRS) in which it used Oriented FAST and rotated BRIEF (ORB) algorithm. ORB makes use of FAST detector and visual descriptor BRIEF (Binary Robust Independent Elementary Features). It comes up with

a swift as well as an effective substitute to Local Scale-Invariant Features (SIFT).In the beginning, some preprocessing actions are carried out on the provided currency paper image. Thereafter, the ROI is extricated out of the surroundings. For feature recognition and illustration of the image that has been provided , the ORB Algorithm has been used .And then, for matching binary descriptors procured from the extraction phase of the feature, Hamming Distance has been used.

The authors, [2] have proposed a framework focused on basic utilities of image processing. The basic methods used throughout their proposed system involve segmentation of the image foreground, enhancement of the histogram, detection of the region of interest (ROI) and thus eventually comparing the template on the basis of cross-correlation between both the image procured and the dataset.The research outcomes indicates that the methodology recognizes Egyptian capital with a precision of 89%.

The authors, [3] have presented a Currency Recognition System on the basis of Oriented FAST and rotated YoloV3 algorithm. They preprocessed and converted the RGB image into the grayscale image. After pre-processing, a Sobel algorithm was applied for extraction of the inner as well as the outer edges of the image. Clustering was done using the YOLO V3 algorithm in which it forms the clustering of features one by one and after that shows the result of the currency value.

The authors, [4] have presented a framework for fake currency detection.Using a realtime image captured from a web camera, this framework can identify Indian currency notes. The key goal of the system is image processing technology and thus using it to inspect authentic currency notes.By extracting the characteristics of notes, this software system can recognise the fake currency.The rate of success of this software system can be calculated in terms of precision and pace. MATLAB, image processing, edge Detection, CNN and Surf are the main technologies used.

The Author [5] in their Journal Computers in Industry by Springer they have suggested a novel work method for identification of Indian currency notes by following a modular approach. This suggested work collects unique and distinct characteristics of Indian banknotes, such as RBI seal, central numeral, identification mark and colour band for the visually challenged and uses specialized algorithms to detect each particular feature. The suggested mobile-based Indian currency detection model uses image processing for feature extraction and a simple CNN for currency detection using the provided feature inputs data. The Core Technologies used in this system may be Mobile Application, Edge Detection, CNN. The Author [6] in their Journal International conference on Computer science, Communication. and security by Springer proposed a structure for the visually challenged and foreign visitors of India who many times find it difficult to recognize various types of banknotes. This proposed paper uses deep learning techniques and a detection model which is trained with a dataset. In this paper, the author chooses faster RCNN which helps train models and identifies Indian banknotes quite well, which helps visually challenged people, foreigners and old people. The

Tools and Technology used in this module is Python Programming Languages, TensorFlow, Image Processing

The Author [7] "CrashSafe: have studied the UI and its effect on people's experience. An unsatisfactory user interface often leads to a large number of user complaints. Systems with such faults put the dependability of software at risk. Due to the app's poor response, users give it a low rating. Users could have various expectations regarding the latency of the UI (e.g., the amount of time between when a user begins an operation and when the UI is updated) in various tasks. The Google website recommends that UI response time should be less than 200ms. Users detest waiting longer than expected.The authors as per this paper, discuss their experiences developing user interfaces for database access to a corporate venture data system for field personnel while working on an industrial project.Size of the screen and screen resolutions vary significantly across devices, as do aspect ratios and the complexity of mobile operations.

The author [8] over 6 million intents against over 800 apps in this article and discovered that around 10% of Android components evaluated crashed as a result of intents. Separately, discovered 1414 open surfaces in 100 Android apps, the majority (1013) of which were triggered by intents. Application crashes are the most common issue (62 percent of all) encountered by users, with the majority of them prompting users to remove the programme. Additionally, we examined 15,000 Google Play apps and discovered that around 16% (337 out of 15,000) were leaking information through mobile application crashes.

The author [9] "TCM: test case mutation to improve crash detection in Android. discussed the significance of GUI testing of mobile applications and proposed Test Case Mutation (TCM). It is a technique for mutating existing test cases in order to generate more diverse test cases. These altered test cases discover crashes that were not identified before by standard test cases. TCM is distinct from the more commonly-familiar Mutation Testing (MT) technique, which involves inserting mutations into the source code of an Application Under Test (AUT) in order to determine the quality of test cases. However in TCM, we augment already present test cases with latest ones in order to improve the count of crashes identified.

The author [10] ―Currency Recognition Using of Image Processing to determine if the banknote is fake or not. The framework is built using the Python programming language. The steps in this procedure, which use appropriate methods, include character extraction, grayscale conversion, segmentation, comparison, edge detection, and so on. This technique evaluates even more characteristics than previous suggested methods in order to extract features. Currency differences are as well shown alongside the result. Counterfeit money, Image Processing, Python programming language, grayscale conversion, edge detection, and segmentation are some of the technologies used in this article.

The author [11] in this paper use the cam scanner, with the aid of a scanner or a camera, the author digitises textual material in this document. It's also possible to use a portable scanner to process information right away. The gathered data and digitised material is sent to OCR, which extracts textual data from a file, which may be a snapshot, a scanned document, or a video clip. The transformation took place only after a machine has obtained the whole collection of files For more study, the OCR uses grayscale versions of the files. Character recognition is achieved based on the strength of the areas in the picture. The lighter areas are considered the backdrop, while the darker areas are considered the text.The alphanumeric values are then identified and categorised using this information. Image de- skewing, despeckling, binarization, line reduction, layout analysis, line and phrase identification, script recognition, character segmentation or separation, scaling, and aspect ratio normalisation are some of the OCR preprocessing techniques.Characters are identified using attribute recognition and pattern detection algorithms. The characteristics of numeric or alphabets are independently told to identify these characters in text through feature detection. To increase the system's performance, complicated formats must be treated, proofreading and simple mistakes must be corrected, and the text must be stored for future use. For the visually disabled person, the voice synthesiser transforms the final material into audio output. This machine artificially generated human voice.

The author [12] uses the ORB Algorithm is used in this paper to propose a mobile-based currency recognition method for vision impared people. To remove the noise, this approach used image processing operations. The related part Algorithm is then used to remove ROI. For obtaining the binary descriptors for storage in the database, the ORB is used. Finally, using the hamming distance method, adapt the findings to the domain descriptors. In terms of processing time and precision, the proposed method outperforms the CRSFVI system, according to the evaluation findings. In coming time, we will work to incorporate more types of banknotes from various countries and develop the process by using other similar strategies so as to increase precision and achieve 100% accuracy.

The author Vincent [13] in this paper demonstrates how a stacked sparse denoising autoencoder that was trained using numerous synthetic examples and which then served as a filter was used to train the image lightening up and denoising functions, which were subsequently used to clean essential shade and corrupted images. According to the findings, deep learning methods are best suited to these kind of activities for natural reduced illumination images of various degradation. The suggested LLNet architecture outperforms existing image increase methods like CLAHE ,histogram equalisation, , hybrid methods and gamma correction like adding HE first and then using a state-of-the-noise reduction like BM3D.While some of these approaches achieve best in amazing cases, our system has been able to adjust as well as carry out number of (illuminating & buzz) scenarios. Also powerful methods of learning mark signals and loud sound mechanisms from shade pictures with out manual processing are deep autoencoders.

The author [14] have worked on an algorithm for banknote recognition in bionic eyeglasses for the visually impaired. Using the following methods, preprocessing and feature detection of the banknotes has been done: binary conversion, tactile mark detection, pattern detection, morphological pre-classification. For classification, the following features have been selected- portrait, shape, colour, tactile mark classification and decision. The features extracted for tactile are mark classification the features are- number of objects, Axis ratio, extent, far away from centre, far away and major Axis ratio. The algorithms have successfully been trail through a mobile phone.

The author 15] have invented a system for currency recognition using image processing. Since it is impossible to recognize all the currencies of the world, the creation of such a system was necessary. Convolution Neural Network(CNN) for object recognition and classification has been used along with TensorFlow Object Detection API which is an open-source schema built on TensorFlow. A model has been generated using a data set that has been split into 80% training and 20% testing. Then CNN has been used to increase the accuracy. For training the dataset faster R-CNN model is used. Its three sections are Convolution Layer, Region Proposal Network and Classes and Bounding Boxes prediction. In Convolution Layer training of filter and computation is done to form a feature map and the faster R-CNN is applied to arrange the features.

The author [16] suggests to use latest techniques to automated speech accolade on the basis of active learning. Active learning requires effective use of particulars that would otherwise be transcribed at a high cost. Furthermore, active learning comes with the ability to modify to non stationary events through a response procedure built into the training algorithm. Active learning is also a test algorithm which selects training data to improve the accuracy of the word. In comparison to random sampling, our investigations have shown the use of active learning reduces by more than 60% the amount of labelled information required for the provided word precision, while also improving word accuracy.The author [17] suggested that(ASR) Automatic Speech Recognition is considered as a tool for at most completing translations from colloquial speech to written wordings, and thus being quite inconvenient. Anyway, thanks to significant advancements in computer science technology & information processing methodology, ASR has become more reliable and manageable, and the amount of applications has grown significantly. A microphone will be used in lieu of a keyboard and mouse in many functions in the near future due to improved natural speech recognition (ASR) technology.a. It seems that clinicians who work with people who have oral communication disorders should be involved in this growth so that their clients can get the most out of this advanced hi-tech technology.

The authors [18] has said that this paper includes using a real-time picture obtained from a web camera, this machine can recognize Indian currency notes. The system's main goal is to use image processing technology to verify the currency notes are valid. By extracting the features of notes, this software system can detect fake currency. This software system's performance rate can be calculated in terms of accuracy and time. MATLAB, image processing, edge detection, CNN, and Surf are some of the main technologies used. The authors [19] suggested that this paper they look at the difficulties that a visually impaired person faces and the solutions that have been proposed to address this issue in recent years. They've also identified a few effective techniques, such as ANN (Artificial Neural Network), and others. They also learned how to identify fake currency using image processing in [10] Madhuri R. Raut, Prof. Dr Krishna. K. Warkhade's article in the International Open Access Journal. First, the image is acquired, and then pre-processing is applied to the image. The picture is then transformed from RGB to HSV. The picture is then segmented and morphological operations are performed on it. Finally, the image's features are extracted.The authors [20] showed that, due to advances in printing technology, the issue of counterfeit currency has grown in recent years. They looked at a variety of fake currency identification methods and algorithms to see what features are available in a currency note that can be used to determine its authenticity.

The authors, [21]in his journal on Reducing the size of the app updates has discussed how the app network traffic can be reduced using DELTA++. He explained how Google built Google Smart Application Update utilising the Delta Encoding Method for this purpose at first, but that it wasn't the best approach. One reason for this is that it only functioned on the Android Application Package (APK) level, whereas DELTA++ may be used on Blackberry, iOS, and other mobile operating systems. Then came DELTA++, a technique for compressing Android application updates using the DELTA (Delta Encoding for Less Traffic for Applications) algorithm. The rsync algorithm, a sort of delta encoding, has been used to reduce network utilisation.So when any update has to be done, the whole version does not get downloaded rather only a part of the version that has got fixed needs to be downloaded.

This saves a lot on the network traffic which thereby decreases the load on the cellular infrastructure.The authors [22] in their paper have worked on the concept of DELTA++. They have also discussed the drawbacks of Google Smart Application and how DELTA ++ overcomes its disadvantages.DELTA++ is a file transfer mechanism that transfers the difference between two files rather than the whole file. It takes as input two files, one old and one fresh, and calculates the difference between them. This distinction is referred to as a "patch." This patch, which is sent, represents the difference between the two files. To construct patches, two tools were developed: UNIX bsdiff and bspatch.These Four steps comprise the application updation process: patch creation, transmission and deployment to the device, and lastly, setup of the upgraded version.Unlike Google Smart Application Update, DELTA++ decompresses the APK before unpacking its individual modules. According to their findings, DELTA++ can significantly reduce the size of application updates by 77 percent on average, compared to a 55 percent drop with Google Smart Application Update.

The authors [23] have developed a money note recognizer that recognises multiple shades of Malaysian banknotes and responds to them by transmitting different sounds for different notes. The aim of this endeavor is to create an attractive, simple, adaptable, and moderately priced device for the visually impaired. The shading sensor for identifying the different shades is a Programmable shading light to recurrence converter (TCS230). The ATMega328P-PU microcontroller is used to sift through the contributions (TCS230). To create the ATMega328P-PU, a model of the Arduino board was developed, as well as an Arduino-independent circuit. The yield sound example is made by using the microcontroller's defer capability. The various banknotes were interpreted by evaluating the yield of various shading light frequencies and dissecting them. By and large, this approach was increasingly beneficial.

The authors [24] have also suggested a method for locating false banknotes that relies on profound learning for visibly disabled persons and visible light images captured by cell phone cameras. CNN is used to identify counterfeit banknotes in the US dollar, euro, krw, and jordan. To increase precision, the nearby ROI is focused on the centre of the banknotes territory and investigated using the class enactment planning method (CAM). There is no need to preorder the banknote group or side. Numerous CNN struc+tures, such as AlexNet, ResNet18, and GoogleNet, were used, and they outperformed previous strategies. The authors [25] have done a study on different crashes specific to android , what caused them and what could be a possible solution to solve different types of crashes. They chose a data where they manually selected the android specific bugs and divided into various categories like App State &UI, Compatibility, Memory etc. Crash causes are largely caused by inability to manage uncommon or exceptional circumstances, inability to upgrade programmes rapidly when platform issues arise, and failing to manage unfavourable circumstances, according to empirical investigations. Hence this study proves that along with addressing to unusual occurrences and bad conditions while the app creation is on, programmers must periodically upgrade applications to accommodate system changes.

The authors [26] incorporated a currency recognition system (CRS) using Oriented FAST and rotated BRIEF (ORB) algorithm. The ORB is based on the FAST detector and visual descriptor BRIEF (Binary Robust Independent Elementary Features). It aims to provide a fast and efficient alternative to Local Scale-Invariant Features (SIFT). Initially, some preprocessing operations are performed on a given currency paper image. Then, important ROI is extracted from the background. The ORB Algorithm is used for a feature detection and description of the input image. Finally, Hamming Distance is used for matching binary descriptors obtained from the feature extraction stage.

The authors [27] proposed a system based on simple image processing utilities. The basic techniques utilized in their proposed system include image foreground segmentation, histogram enhancement, region of interest (ROI) extraction and finally template matching based on the cross-correlation between the captured image and the dataset. The experimental results demonstrate that the proposed method recognized Egyptian currency with an accuracy of 89%. Further in [3], presented a Currency Recognition System based on Oriented FAST and rotated YoloV3 algorithm. They pre-processed and converted the RGB image into the grayscale image. After pre-processing, a Sobel algorithm was applied for extraction of the inner as well as the outer edges of the image. Clustering was done using the YOLO V3 algorithm in which it forms the clustering of features one by one and after that shows the result of the currency value.

The authors, [28] in International Journal of Research in Computer and Communication Technology proposed texture classification for fake Indian currency detection. Automatic Fake Currency Recognition System (AFCRS) is developed to identify a fake currency. This system can be implemented on android phones as well, which makes it easier for a common man. The authors, [29] in his Journal Computers in Industry by Springer proposes a work novel technique for recognition of Indian currency banknotes by adopting a modular approach. This proposed work extracts unique and distinct features of Indian currency notes such as RBI seal, central numeral, identification mark and colour band for the visually impaired and employs algorithms optimized for the detection of each specific feature. The mobile-based Indian currency detection model is the proposed model which will be using image processing for feature extraction and a basic CNN (convolutional neural network) for identification of currency with the given feature inputs. The Core Technologies used in this system may be Mobile Application, Edge Detection, CNN.

The authors, in the International Conference on Machine Learning and Cybernetics proposed different algorithms that can be used to identify monetary value of a currency note for visually impaired people. The main challenge was to find an algorithm which is accurate as well as fast for analysing the monetary value of currency notes. They have focused on 3 algorithms SIFT, SURF and ORB which are available in the OpenCV library of Python. Also, They found that ORB is faster than the other two algorithms to find the monetary value of currency notes.

3. Proposed Work

This research paper has developed an effective way to predict currency note value where we implement a combination of two deep learning techniques CNN and LSTM which is working as a Hybrid approach named as CNN-LSTM. If we use it is the right procedure. Both techniques have their own advantages in this model and help us in predicting with more accuracy.

Fig 1: Background removal from Image

The main characteristics of convolutional layers include their capability of reducing the size by using convolution filter method on RBG 3D matrix data input of images, removal of the blank spaces and the extraction of the practical and the effective knowledge. Whereas, LSTM can be used for effectively identifying the long-term and the short-term dependencies.

The main motive of this proposed model is to present a combination of the benefits of CNN and LSTM deep learning techniques for achieving the desired results. Mainly, this proposed model is named as CNN- LSTM which consists of two major components.

The first major component includes pooling and convolutional layers which further consists of complex mathematical operations for developing features on the input data. Furthermore, the second component makes use of the LSTM and dense layer's generated features. Finally, the core of the proposed model i.e., LSTM, pooling and convolutional layers are described briefly.

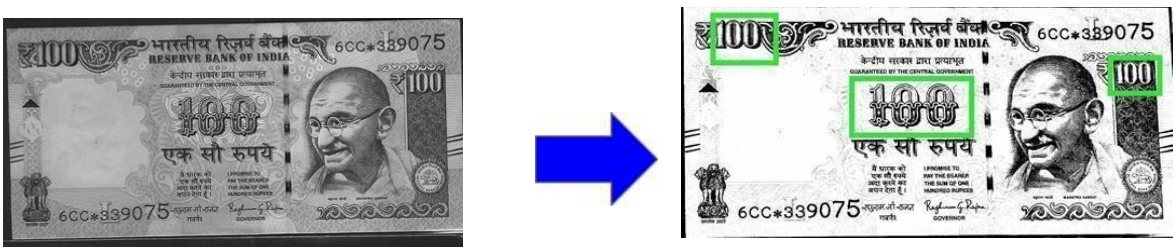

Fig 2: Image Segmentation

3.1 Convolutional Neural Network

Convolutional neural network (CNN) is a neural network having a deep structure and expertise in resolving and dealing with issues related to images [31].

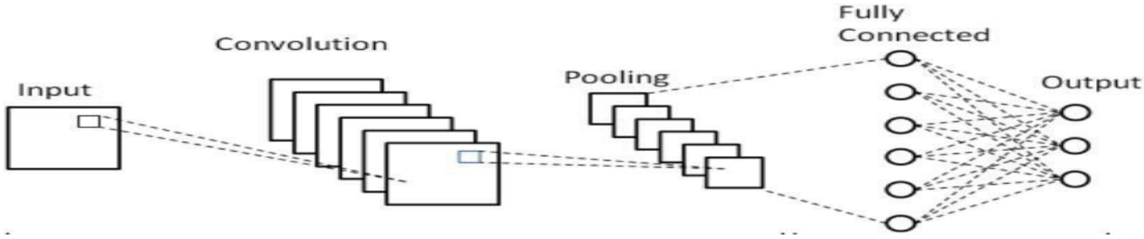

Fig 3: CNN Model

3.2 About Convolutional and Pooling Layers

Convolutional and pooling layers are mainly drafted for pre-evaluating of data. These layers are responsible for filtering out the data that has been inserted and withdrawing the beneficial and the important information which has to be further put in a completely linked network layer of CNN.

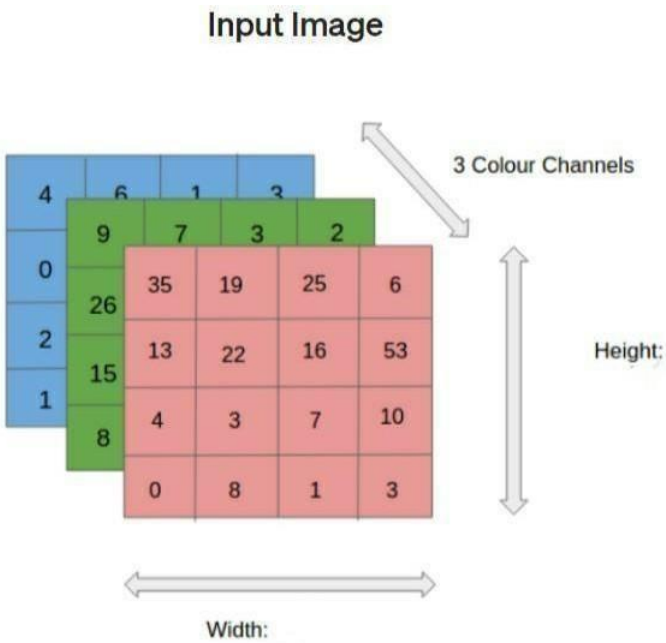

Fig 4: Input Image in RGB format

Moreover, the main function of convolutional layers is to assist the application of convolution operations between the unprocessed input data and the production of new features values by the convolution kernels. In addition, it is important to consider the input dataset must be in a structured form of a matrix as this technique only allows the extraction of features only from image datasets. Furthermore, the convolution kernel can also be referred to as a small window (in comparison to the huge input matrix) that consists of the coefficient values in a matrix form.

The kernel then puts in convolution operation on every other sub-region by sliding all over the input matrix such that the particular window intersects the input data matrix. Therefore, a convolved matrix is derived as an output of all these operations. This convolved matrix also represents a specific feature value which is stated by the dimensions of the filter applied and the coefficient values. Furthermore, the generation of multiple convolved features can be done by application of various convolution kernels on the input dataset. Moreover, these multiple convolved features are more helpful as compared to the original feature of the input data which in turn improves the model's overall performance.

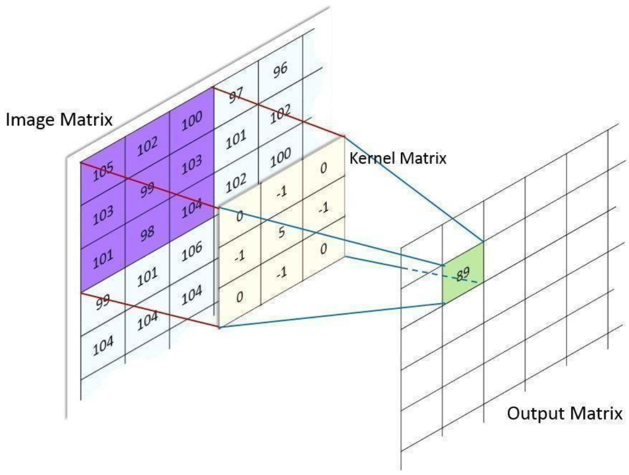

Fig 5: Convolution Operation

3.3 LSTM Layers

One of the major advantages of using LSTM over the standard RNN is the additional gating mechanism. This gating mechanism consists of the input gate, output gate and the forget gate for controlling the information transmission between the neural networks. This structure further enables the LSTM to manage and create an administered flow of information by helping to decide whether information has to be "remember" or "forget", hence resulting in the learning of long term dependencies. The architecture of the LSTM unit can be described by the state diagram in Fig. 6.

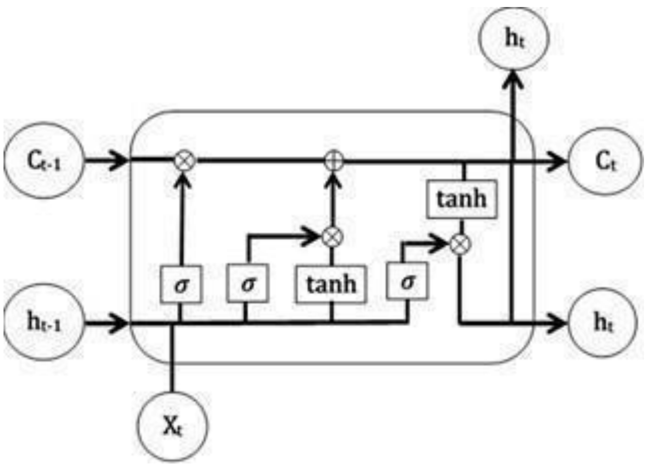

Fig 6: Architecture of LSTM Model

The forget gate contains a sigmoid layer that gets hold of the last hidden state (ht−1) and current input (xt) to generate an output in range of 0 and 1. Basically, this layer determines what data is to be retained or deleted. Here zero value indicates that we have to forget the previous values and one indicates to keep the previous values. The output for forget gate is as given in eq. 1

$$ft = b*f + \sigma*W*[ht-1, xt] \quad \ldots 1$$

After that, the forget gateway uses combinedly tanh and sigmoid functions to determine which data will be entered into the cell state. Both of these functions get ht - 1 and xt as input. The sigmoid output determines whether or not the existing data is useful, and the tanh function controls the system by subtracting the figures in range of -1 and +1. Then finally, both results are multiplied as given in eq. 2 and 3

$$it = (bi + Wi*[ht-1, xt])*\sigma \quad \ldots 2$$

$$Ct = \tanh(bc + WC*[ht-1, xt]) \quad \ldots 3$$

This data then gets replaced with the output from the forget gate and input gate in the cell state. It’s done with a clear repetition of the current state of the cell and the removal of the forget gate. In the case of ft is 0, zero will also be the outcome of the product, thus implying a complete decrease in the previous value. Else, if ft is 1. Then, it’s retained. After that, the cell state is updated by pointwise addition. As given in eq. 4

$$Ct = (it \times Ct) +(ft \times Ct-1) \quad \ldots 4$$

The output gate determines the final output is the final stage. This result also serves as a concealed state later on, ht.It takes ht−1 and xt as the input and the status of current cell state Ct is forwarded with the help of tanh function in this gate. After that, both sigmoid and tanh outputs are multiplied to find out what information would be stored inside the hidden layer. As given in eq. 5

$$St = \sigma(Wo*[ht-1, xt] + bo) \; ht = \tanh(Ct) \text{ x } St \quad \ldots 5$$

3.4 CNN-LSTM Model

We utilized versions of the proposed model in our implementation. The CNN–LSTM model contains convolutional layers that are succeeded by a pooling layer, an output layer and LSTM layer of one neuron. CNN-LSTM outline is given below in the Fig 7.

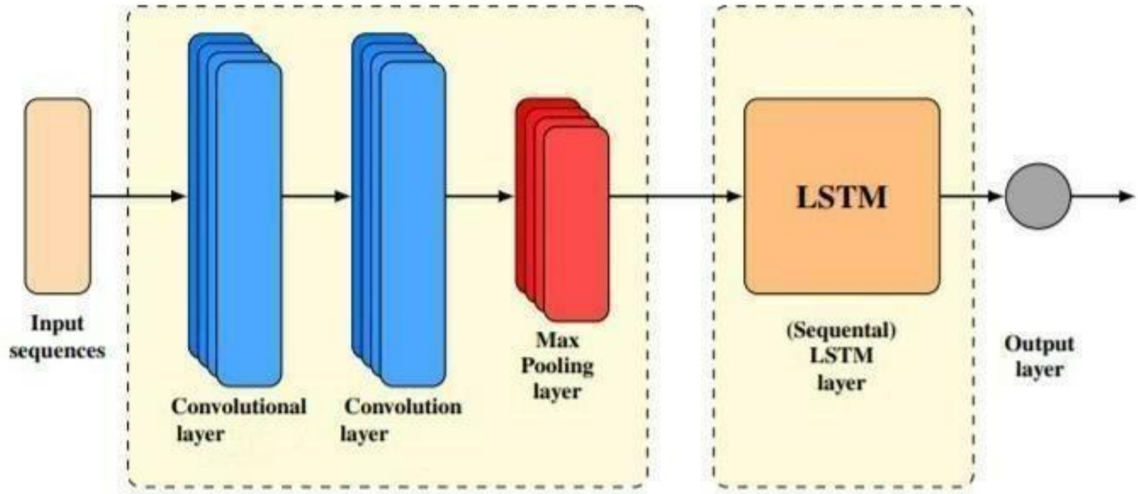

Fig 7: CNN-LSTM Model

3.5 Cloud Model Deployment

Our previous system was based on the model that was directly deployed in an android mobile app which made it slower in terms of speed and heavy in terms of size and gave problems like frequent app crashing. We couldn't even get to know when the crash occurred because apps usually crash without giving any warning or error messages. And error messages are something which gives developers a way to fix it.

Now, In the current system, We will implement a model on the cloud which will help us to reduce the app size, make our app fast, and most importantly we can update our model in production without updating the app on the playstore. Current model is going to be implemented in Google MLOps Cloud service which will be having the following benefits-

- Straightforward management of infrastructure
- Better scalability
- Price is less
- Always available

3.6 Crash Detection System

Our Previous system was based on mobile computation which wasn't giving up to the mark performance as it was processing everything on a mobile. The problem being that mobile phones have only a limited memory and processing power, no matter how good the smartphone is. Hence, to improve on this ,we will implement a crash detection system which will help in getting errors sources and stack tracing of applications at the time of crash in mobile applications. It will also give us data about a particular device which has been getting frequent crashes so that we can analyse it and improve the software easily.

We'll also use Google Crashlytics, a lightweight, real-time crash reporter that will help us track, prioritise, and resolve stability issues that are affecting the app's quality. It also helps you save time troubleshooting by automatically grouping crashes and highlighting the events that led up to them.

3.7 Enhanced Camera Scanning Functionality

Our Previous system was based on default native scanner api available on android development platform which was not compatible with all types of lighting conditions. Now, We will be testing different third party packages available on android platform that can be made by an individual or a community. Its implementation in our current system will help us achieve better results.

Image alignment and stitching techniques will be adapted with other image processing methods to stitch together closely captured images of portions of a page. Then the images will be passed into an image stitching pipeline which will extract and match the features in the images, perform bundle adjustment and warp the images together.

3.8 Converting the text result to corresponding audio message

TTS (Text-To-Speech) allows an Android smartphone to "speak" text in a variety of languages. A number of languages are supported by the Android platform's TTS engine. Although the engine has all Android devices supporting TTS, certain equipments possess finite space and may lack language-specific resource files .The TTS API permits an application to request that language files are available from the platform and to start downloading and installing, When a user wishes to install the resources. The TTS engine keeps track of all the entries that need to be synthesized in a global queue. Every TextToSpeech instance may check which expressions disrupt the present one and are just queued by managing their own queue. The initial proposal for a speech might stop everything that was being synthesized currently: the queue would be smoothed out, the latest utterance would be torn into the queue and put it on the front of the line and the text message would be transformed to its matching audio message.

4. Result

We have successfully completed our goal to create and depict a system which can be utilized to identify currency for a visually impaired user. We have translated the system to a smart phone technology, performing around strain like restricted computing capacity and memory, we bestow an application for recognizing currency bills using computer visual system and techniques, that can run on a affordable smartphone. while still attain great accuracy and little stated time.

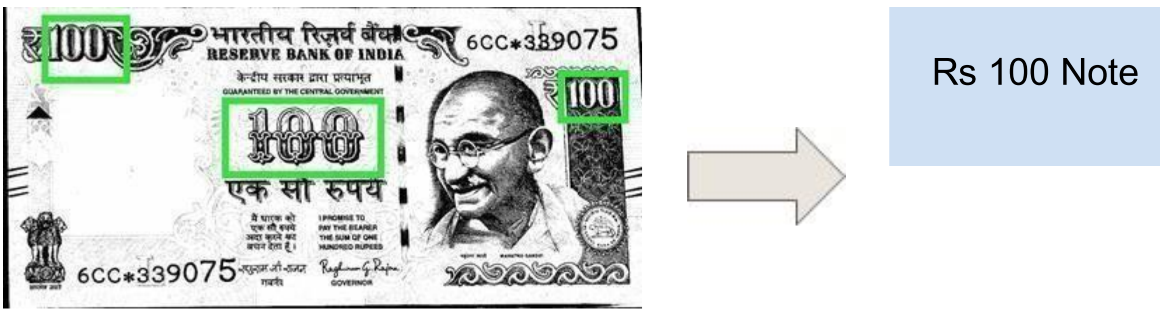

Fig 8: Image Recognition

The enforcement of the proposed system has been estimated using the advanced dataset of 300 images. In the assessment, the authors try out a database of 300 indian banknotes, which includes 5 kinds of banknotes (2000,500,200,100,50,10).

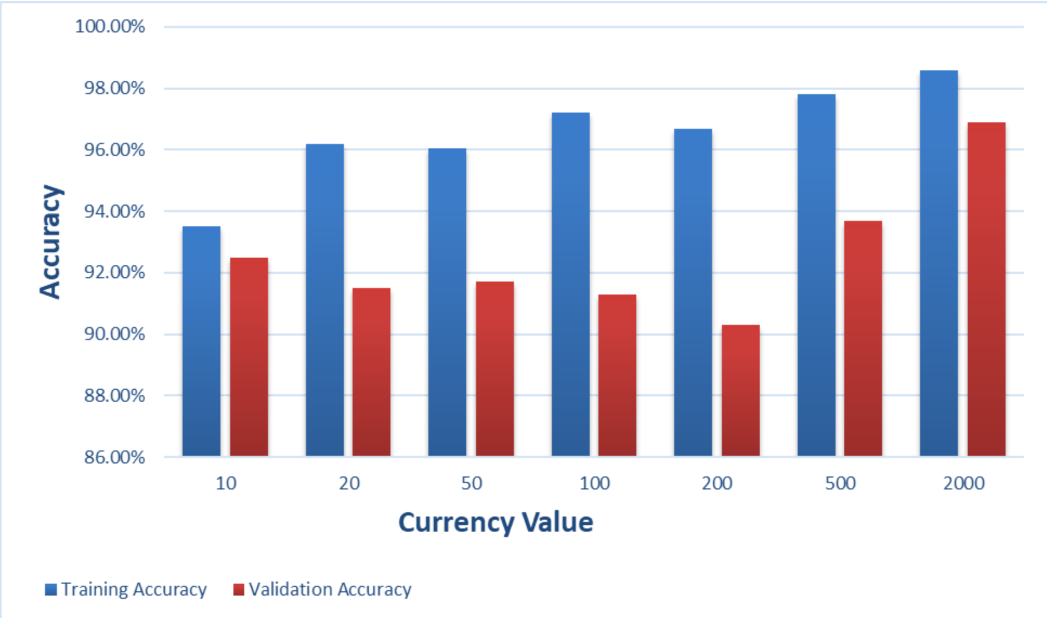

Fig 9: Accuracy Curve for CNN-LSTM

TABLE 1) Accuracy of the Proposed System

Currency Value	Training Accuracy	Validation Accuracy
10	93.5%	92.5%
20	96.2%	91.5%
50	96.05%	91.7%
100	97.2%	91.3%
200	96.67%	90.3%
500	97.8%	93.7%
2000	98.6%	96.9%

In order to recognize the denomination of the currency we compare the extracted features with the available datasets**.** The recognized text are recorded in the form of script files. Then we make use of the text to speech converter to load these files and display the audio output of text information. Visually impaired or Blind users can adjust the generated audio accordingly based on their preferences which includes speech rate, volume and language. The earlier model used to show a little spike in the accuracy of that proposed system, but our model is used to show 92.55% of an accuracy.

5. Conclusion

Currency recognition system (CRS) built on hybrid of Long short-term memory (LSTM) and Convolutional neural network (CNN) obtained highly accurate results and with very less computational time. Adding cloud deployment and crashlyitcs functionalities further made the system more robust irrespective of the camera quality and lighting conditions. The innovative outcome have shown the success of hybrid CNN- LSTM algorithm in general for Indian banknote currency recognition, while our algorithm is tested in a better challenging dataset with the images taken in contrasting circumstances. As a result, the results indicates the accuracy and speed of the CNN-LSTM technique, which can be applied in real-world scenarios to assist visually impaired people with monetary transactions.

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DESIGNING HYBRID SIMILARITY BASED SEARCH ENGINE USING ARTIFICIAL INTELLIGENCE

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Abstract— In the 20th century it is been observed that there is drastic increase of information on web and the biggest reason for that is the availability of computation and content transferring on internet is increasing and it is not a less known fact that everybody is seeking for the most relevant information , it is been already know that since the beginning of the era of internet the search is quite a challenging problem and also a necessary problem to solve , however there are already plenty of solutions available for the search engines and they are serving us quite well but as the searching content and the users seeking for the content is increasing second by second it became necessary for us to move forward and experiment other techniques as well , best way to compare two sentences is to compare their similarities there are basically 2 types of similarities word based and semantic based similarity nowadays search engines are been built on either of similarity and in this paper we will see how can we implement a powerful search technique which leverages both the techniques , ideally semantic based similarity is a machine learning based technique which uses encoder model to generate semantic vector which are discussed in more detailed manner in the paper , another dimension that we shouldn't ignore while solving this problem is time it is important to understand that user will spend more time
.

Keywords—Machine Learning , Artificial intelligence, NLP, LSTM, Search Engine, Encoder Model, Deep learning, Bert, Universal Vector Encoder

1. INTRODUCTION

In the era of technology where world is moving towards web. Digital content has become new source of knowledge gaining however with respect to digital content the complexity of solving the searching problem is also increasing. As era change, it is been observed that the innovations are not only coming from one domain but from several domains. It also became necessary to provide the best possible search results for the given query that too in an optimized manner. In content searching it is a necessary for any business to give their users provide the most relevant results. There are many deep learning architectures[1] which can be used to generate some quality search results as these models are already pre-trained on lots of text data .The pre-trained models are specifically designed to extract the semantic information from the text which could be used to compute the semantic similarity [2]. However, there is exhaustive number of techniques to compute the similarity between two points [3]. There is another very simple technique called word based similarity [4]. Another approach could be to combine the both mentioned similarity techniques. However, combining the results will not be as trivial as it sounds so we will experiment the techniques in order to get the best possible output. Another aspect for the problem is the latency where we already know the user will not even spend more than 0.5 second for the results. To tackle the latency problem we will be employing the technique called inverted indices [5].The main aim of this study is to solve the above stated problem using some machine learning techniques and software engineering approaches by using the data of the stack overflow to give relevant search results to the user. One of the major key points which should be taken into the consideration is the latency requirement for the above problem is that, the user will not spend more than half a second to get the results so the latency requirement for this problem would be less than 0.5 second. So objective of the search engine is to give most relevant results from the available answered questions to the user using the similarity based techniques in a computationally optimized manner. So from the design stand point we will be building a Q/A search engine which on the run time takes the query question as text and give the most similar answered by using the text and the semantic similarity of the query as results to the user in less than 0.5 second.

2. Related Review

This section will discuss about the different researches uses and comparison of previous search engines models used in internet search.

In [6], the author proposed a method for converting node to vector in a graph, they named it node2vec. The author proposed this technique to convert each of the node of the graph to a vector. The author discussed about feature learning in graph can be done using the optimization of graphs. It also explains the exploration-exploitation trade-off on different search techniques. In [7], author proposed an algorithm to traverse the data randomly in a graph network, they called it Random Walk. The author discussed about how to generate embedding from randomly created paths. The author also discussed about the useful of randomness in creating the paths of graph networks. In [8], author proposed a research about the role of matrix factorization in recommender system. The author discussed about the collaborative filtering and how it can be used for recommendation system just by shaping the problem in the optimization problem. The author states that matrix factorization plays vital role in reducing the dimensionality of the data.

In [9], the author proposed architecture of Docker, in the proposed work author discussed about its comparison with the virtual machines. In the proposed research work the author shows how Docker can be used to experiment different environment through docker images and can be contained in the container of a docker as an instance. The author also shows that how docker can be a light alternative to the virtual machines and also how docker containers can be computational efficient against virtual machines. In [10] discussed about a search engine called Elastic search, in the proposed work the author discussed about the ways of searching through a data corpus. The author also discussed about the optimizations which can be effective and useful in the search. In [11] author discussed about a technique using which we can generate the similarity between 2 sentences, named as word based similarity. In [12] author discussed about a technique which can be used to generate the similarity score between two sentences using semantics of the sentences, they named it sentence based similarity.

In [13], the author discussed about deep learning architecture using which we could generate a semantically stable embedding for the sentences. They named it as Encoder model , The author proposed this algorithm with feeding the sentences as a different time steps sequentially. In [14], the author discussed about a encoding technique called word2vec. The author states that technique could be used to generate semantically stable embedding from a single word. In [15], the author proposed and discussed some techniques on computation of similarities which is ideally proposed for the recommender system. The author also discussed about the advantages and disadvantages of the techniques.

In [16] the author discussed about the different aspects of exploratory data analysis. In the proposed work, the author mentioned different methods to visualize and interpret from the plots and graphs. In [17] the author discussed about the preprocessing techniques which can be useful for the natural language data. In the proposed work the author pointed out different preprocessing methodologies for different types of data.

3. METHODOLOGY USED 3.1.Dataset Used

Dataset has been collected from stack overflow data dump [18]. The dataset has been further divided into more than 200 categories out of that four categories is been used for the further analysis of this paper that is Computer Science, math, data science, artificial intelligence. Each category contains the questions and answers related to their name. Each category has a single XML file contains following attributes • Id : Feature contains the unique values of each posts.

- PostTypeId: It shows the type of post (in case of answers PostTypeId is 2 in case for questions it is 1)
- ParentId: It contains the values which shows what is the ParentId of the Post (For answers ParentId is the Id of its Question)
- Body: It contains the text it can be Question or Answer.
- Title: It contains the Title of the Post
- AnswersCount: It contains the values showing how many number of Answers Are there.
- Tags: It contains the Tags of the Post.
- Category: Shows Which Category it belongs to.
- CreationDate: Shows the Date and Time of the Post Creation

Out of the following attributes only some attributes are of use for building our models i.e., Body, Title.

3.2. Exploratory Data Analysis

This section is about the analysis which is done on the data to get the useful insights which can be helpful for the search engine problem. Firstly data must be downloaded from stack overflow data dump. As our data is in the XML files so we have to make sure that our data takes shape of necessary format. Exploratory data analysis needs be applied on our data so that the insights of the data could be fetched in order to build robust search engine.

Elastic Search is employed which is containerized in a docker Instance. A data dictionary is used which contains each key as unique id for the question and values as a title and answers for the fast retrieval of the questions using ids, so as we will be combining the title, question and answer and then this data will be fed to the elastic search which is containerized in docker. Exploratory data analysis is a crucial step before building a solution for a business problem. So some plots and graphs are plotted in order understand our problem better. Figure 1 shows the Number of questions versus year plot. Figure 2 shows the Number of answers versus years plot.

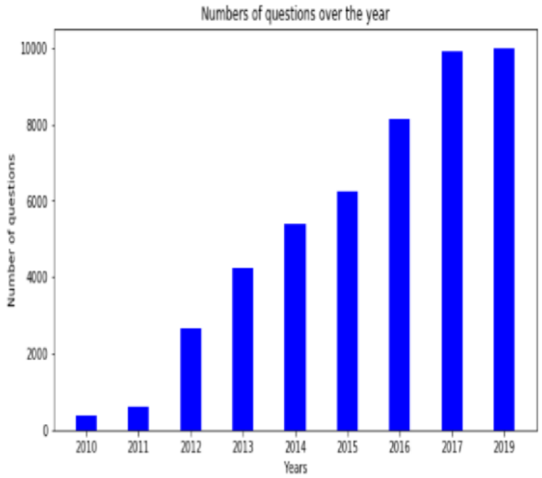

Figure 1: Numbers of Questions over the year

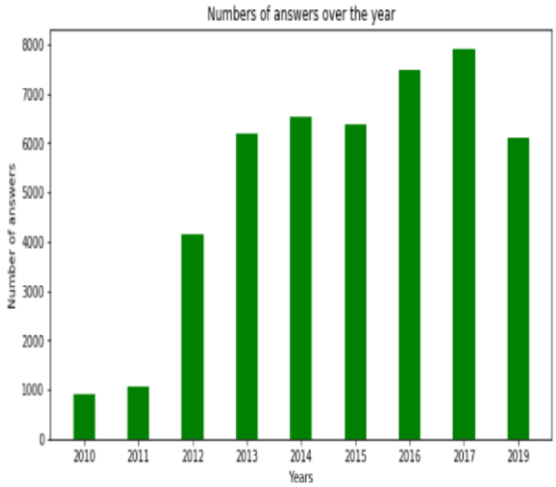

Figure 2: Number of answers over the years

Figure 3 shows the Number of unanswered questions vs years plot. Figure 4 shows the Number of Questions from each category plot.

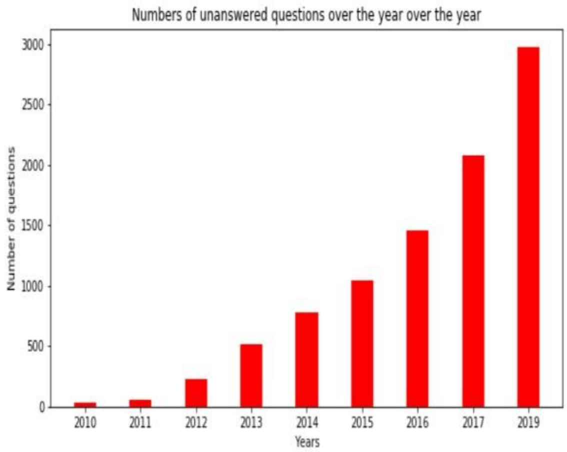

Figure 3: Number of unanswered Questions Over the Year

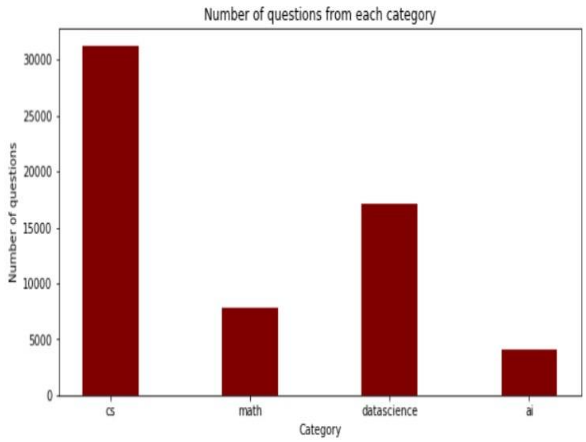

Figure 4: Number of Questions from each category

Figure 5 shows the Questions Word Cloud. Figure 6 Answers Word cloud.

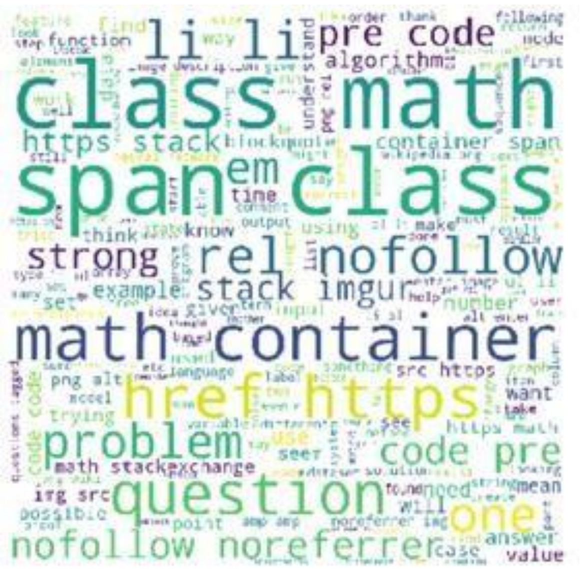

Figure 5: Questions Word Cloud

Figure 6: Answers Word cloud

3.3. Proposed Model

This section discuss about the proposed model of the search engine which is used in this paper to build search engine. Firstly a query text will get embedded through our encoder and then both our search text and embedding would be passed to elastic search container independently to get the score and then it will get added using weighted sum and on the basis of that we will select the answers having top 10 scores. The model depicted in this section includes the all the bits and pieces used and discussed in the above sections. Finalized model can inferred from Figure 7.

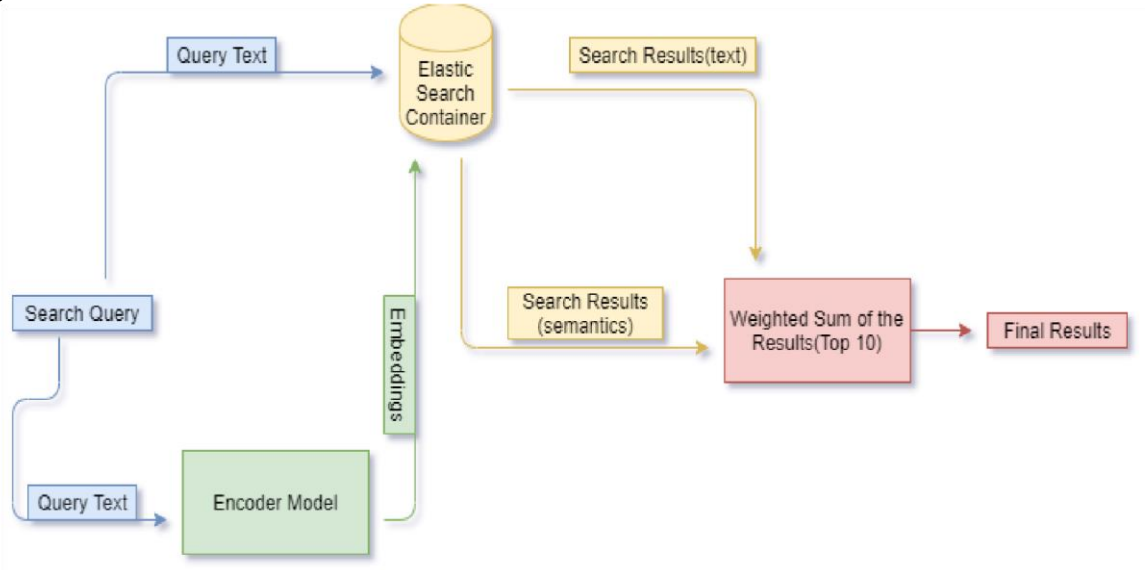

Figure 7: Hybrid search engine model

4. EXPERIMENTAL RESULT ANALYSIS

This section will discuss about the results and analysis of different models used in this paper for building the architecture

4.1. Universal Sentence Encoder Model

In this section we are using the Universal-sentence-encoder to generate our embedding. The universal sentence encoder model is the state of the art NLP model which encodes sentences into embedding. The model takes a sequence or sentence as input and returns 512-dimensional data for each query text. After feeding your data to elastic search we need to define a search function. Search function gets the text based similarity scores and semantic based similarity scores and combines them with weighted average by giving more weight to semantic similarity scores than word based similarity scores. Figure 8 defines the result from Universal Sentence Encoder Model if the question is "*what is red black trees?*"

```
----------------------------Answer No:1------------------------------
title :  why should leaf nodes in a red-black tree be black?
question : from the property of red-black trees we know that:  all
leaves (nil) are black. (all leaves are same color as the root.)
(comren et al "introduction to algorithms")  but what is the reason
that we should enforce them as black, even though they're nill's?
subanswer 1 : take a uncolored leaf node, now you can color it as
either red or black. if you colored it as red then you may have
chance that your immediate ancestor is also red which is
contradicting(according to basic principle). if you color it as black
then no problem even though the immediate ancestor is red. and also
no change in the number of black nodes from root to leaf paths(i.e
every path get +1). this may be the possible reason behind that.
subanswer 2 : it's simply a part of the definition of a red-black
tree. it is also necessary to maintain one of the other rules
associated with red-black trees: if a node is red, then both its
children are black.
---------------------------Answer No:2------------------------------
title :  red black tree clarification
question : i am quite new to red-black trees, and therefore i am
having a bit of difficult time trying to understand them.one of the
properties of the red-black tree is that every red vertex must have
two black children, meaning one cannot have two consecutive red
vertices.can someone explain to me why this is an essential property?
what are the benefits of having such a property?
subanswer 1 : the properties of a red black tree allow insertion,
deletion and search in $o(log(n))$. i guess you can find a prove
online somewhere. when an element is inserted or deleted. a fix-up is
done, it involves rotations in a tree, so the properties still hold.
this ensures the tree is quitebalanced at all times and search is
quite fast at all times.
subanswer 2 : if you check the proof height-balancedness of red-black
trees, you'll see that we essentially analyse the black-height $h_b$
of the tree which, by another important invariant, is the number of
black nodes from the root to any leaf.the property you cite then
gives us the right half of$\qquad\displaystyle h_b(t) \leq h(t) \leq
2h_b(t)$,which allows us to carry over bounds on black-height to
usual height.
--------------------------Answer No:3-------------------------------
title :  root color of a black red tree
question : it is required that, in a black red tree, the color for
the root is always black. however, wikipedia argues that this rule
can be omitted as a red root can always be changed to black but not
vice versa. i get the first half, that a red root can be changed to
black at any time, but in what circumstance is it impossible to
change a black node to red?for instance, consider the branch: black--
red--black--red--black. we can always change it to red--black--black-
-red--black, since a black node does not need to have red children.
subanswer 1 : the root colour of a red-black tree carries no
significance. in fact, you can save memory by not encoding it.
didactically, it is meaningful to talk about a root's colour to
illustrate what it means to be red or black, because it is a special
case because it has no parent which is going to count it when it
evaluates the sixth restriction in wikipedia's list (that the path
from a particular node to a leaf should contain the same number of
black nodes).as for your more general question about when changing a
black node to a red one is allowed: a set of nodes can be repainted
if afterwards, the black-height criterion is still satisfied. for
example, if a row of the tree is saturated (if it is at depth $k$,
there are $2^{k}$ nodes), then you can colour that row black. you may
not colour only part of a (saturated or not) red row black. another
```

Figure 8: Universal Vector Encoder Result

4.2.Analysis using Bi-directional Encoder Representations from Transformers

This section discusses about the results and analysis of model using Bi-directional Encoder Representations from Transformer (BERT). We are using the BERT to generate our embedding**,** BERT Is a transformer based model which encodes text into embedding. The model takes a sequence or sentence as input and returns 512-dimensional data for each query text. After feeding your data to elastic search we need to define a search function. Search function gets the text based similarity scores and semantic based similarity scores and combines them with weighted average by giving more weight to semantic similarity scores than word based similarity scores. Figure 8 defines the result from Universal Sentence

Encoder Model if the question is "*what is red black trees?"*

```
------------------------------Answer No:1------------------------------
title :  why should leaf nodes in a red-black tree be black?
question : from the property of red-black trees we know that:  all
leaves (nil) are black. (all leaves are same color as the root.)
(comren et al "introduction to algorithms")  but what is the reason
that we should enforce them as black, even though they're nill's?
subanswer 1 : take a uncolored leaf node, now you can color it as
either red or black. if you colored it as red then you may have
chance that your immediate ancestor is also red which is
contradicting(according to basic principle). if you color it as black
then no problem even though the immediate ancestor is red. and also
no change in the number of black nodes from root to leaf paths(i.e
every path get +1). this may be the possible reason behind that.
subanswer 2 : it's simply a part of the definition of a red-black
tree. it is also necessary to maintain one of the other rules
associated with red-black trees: if a node is red, then both its
children are black.
---------------------------Answer No:2---------------------------------
title :  red black tree clarification  question : i am quite new to
red-black trees, and therefore i am having a bit of difficult time
trying to understand them.one of the properties of the red-black tree
is that every red vertex must have two black children, meaning one
cannot have two consecutive red vertices.can someone explain to me
why this is an essential property? what are the benefits of having
such a property?
subanswer 1 : the properties of a red black tree allow insertion,
deletion and search in $o(log(n))$. i guess you can find a prove
online somewhere. when an element is inserted or deleted. a fix-up is
done, it involves rotations in a tree, so the properties still hold.
this ensures the tree is quitebalanced at all times and search is
quite fast at all times.
subanswer 2 : if you check the proof height-balancedness of red-black
trees, you'll see that we essentially analyse the black-height $h_b$
of the tree which, by another important invariant, is the number of
black nodes from the root to any leaf.the property you cite then
gives us the right half of$\qquad\displaystyle h_b(t) \leq h(t) \leq
2h_b(t)$,which allows us to carry over bounds on black-height to
usual height.
 --------------------------Answer No:3---------------------------------
title :  root color of a black red tree
question : it is required that, in a black red tree, the color for
the root is always black. however, wikipedia argues that this rule
can be omitted as a red root can always be changed to black but not
vice versa. i get the first half, that a red root can be changed to
black at any time, but in what circumstance is it impossible to
change a black node to red?for instance, consider the branch: black--
red--black--red--black. we can always change it to red--black--black-
-red--black, since a black node does not need to have red children.
subanswer 1 : the root colour of a red-black tree carries no
significance. in fact, you can save memory by not encoding it.
didactically, it is meaningful to talk about a root's colour to
illustrate what it means to be red or black, because it is a special
case because it has no parent which is going to count it when it
evaluates the sixth restriction in wikipedia's list (that the path
from a particular node to a leaf should contain the same number of
black nodes).as for your more general question about when changing a
black node to a red one is allowed: a set of nodes can be repainted
if afterwards, the black-height criterion is still satisfied. for
example, if a row of the tree is saturated (if it is at depth $k$,
there are $2^{k}$ nodes), then you can colour that row black. you may
not colour only part of a (saturated or not) red row black. another
```

Figure 9: BERT Encoder Result

4.3. Discussion

On the Basis of the above results shown in Figure 8 and Figure 9 this has been shown that the results are very similar in terms of quality. It is been also observed that model BERT model is quite complex and requires somewhat slightly more time in order to generate the results than universal vector encoder model so it is better choice to proceed with the universal vector encoder model.

5. CONCLUSION AND FUTURE SCOPE

In this paper, universal sentence encoder and BERT technique has been used for the analysis of this hybrid similarity search engine. On the Basis of execution analysis it is been noticed that due to the complexity of BERT model the execution time for BERT in greater than the Universal Sentence encoder. The techniques which are used in this paper are latest state of the art techniques but there some methods which might be useful for the whole project. We know that we have around 1 lakh data points but the quality of the results could even increase if we feed more data to our Model. As of now the universal encoder model is trained on general dataset but not on the programming codes so the relevancy of results could increase if we train our encoder model with some programming codes data. The technique used to combine the semantic and word based similarity results are weighting average but we could look for some techniques to combine the both similarity scores.

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COVID-19 DETECTION BASED ON DEEP LEARNING FEATURE EXTRACTION AND ADABOOST ENSEMBLE CLASSIFIER

AdaBoost Ensemble Classifier

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Abstract: In January 2020 the World Health Organization (WHO) declared the deadly disease Corona Virus 2 (SARSCoV-2) or (COVID-19) as a global pandemic. The adopted benchmark test results for the detection of COVID-19 is Reverse Transcription Polymerase Chain Reaction (RT- PCR). The test is time consuming and expensive as well. With the nature of the virus, a rapid and efficient way of testing is needed. With the application of medical imaging in different fields of medicine and with the success of Artificial models in many fields of medicine, COVID-19 detection using Computed Tomography (CT) scan images can serve as an alternative to the RT-PCR test, as CT scan images are used in profiling COVID-19 patients in hospitals. In this study, two types of training were performed on three different pre-trained deep learning models namely ResNet-50, ResNet101, and VGG16 by employing the Transfer learning method, in the first training feature extraction and classification were carried out by the pre-trained models, while in the second training, features were extracted utilizing the pre-trained models feature extraction part and AdaBoost ensemble classifier for classification. ResNet-50 with the AdaBoost ensemble classifier outperformed the state of the art models employed on the same dataset.

Keywords: Artificial Intelligence; CT Scan; COVID-19; AdaBoost Ensemble.

1. Introduction

In December 2019, a deadly respiratory disease Corona Virus 2 (SARS-CoV-2)/(COVID-19) which was different from SARS-CoV and MERS-CoV was reported in Wuhan, Hubei Province, China [1] the disease spread was suspected to have started from wild animals which are illegally sold in a seafood market in Wuhan, in few days the deadly disease spread to many cities in China and other countries [2]. On 30th January 2020, World Health Organization declared SARS-CoV-2 as a global pandemic [3], By 16th of march 2020, the number of active and death cases reported in the world was 168,826 and 6,503[4], and by the 27th of August 2020 the confirmed cases reaches 24,514,320 and total death of 832,660, the rate of infection is increasing exponentially, the common symptoms of the disease include fever, dry cough, fatigue, lymphopenia and acute respiratory distress with severe pneumonia[5]. A very rapid and efficient method of detecting COVID-19 is needed to curve the spread of the virus as it affects the whole world.

Due to the widespread COVID-19 in the world, fast and early detection of COVID-19 and the low-cost test is very important, many people have been isolated because they show mild symptoms and the virus has an incubation period of 14 days [6]. The benchmark test result for COVID-19 today is RT- PCR test for the detection of the nucleic acid forms stem from the COVID-19 [7]. The test is performed by collecting respiratory specimens such as oropharyngeal swabs, in the receiving place of specimen human error can occur[8]. The PCR test is time-consuming and costly, patients awaiting results must be isolated which will increase cost either to the government or patient, also the chances of getting the correct result are 30% -50% [9]. An alternate to PCR is medical imaging whereby Computed Tomography (CT) scan images can be applied most especially in the case of pregnant and small children [10], [11]. Though CT is associated with high dosage and is also costly [12] but was used for COVID-19 evaluation and profiling in [12][10]. [10][13]recommended Xray than a CT scan but did not consider pregnant women and children.

1.1. Related works

The deadly disease of COVID-19 still has an impact on the world by crippling activities [14]. Several approaches have been taken into account in tackling the spread of deadly disease [15]. Mathematical models have been analyzed to predict the spread of disease by considering the number of infected, susceptible and recovered patients [16], and this modelling is a classic approach [17]. To achieve real-time prediction, AI models coupled with IoT have been used to help medical practitioners diagnose and monitor COVID-19 by looking at parameters such as temperature, blood pressure, and heart rate, given the high number of cases, the privacy of data transmission and the energy efficiency of the low-power device used to collect information is very important, as proposed by [18], to have an efficient system for patients data privacy, power consumption efficiency, and transmission. To reduce the effect of the economic impact caused by COVID-19. In [19], they proposed an AI model that is data-driven to predict lock-down and nonlock-down area boundaries to reduce the economic impact of the COVID-19 pandemic, the adopted method of lock-down by many countries was a total lock-down, this method is not good for the economy, with the proposed model [19], A near-real-time prediction of areas with high active cases has been predicted and can serve as an avenue for smart cities. [20] IoT based system was proposed to identify COVID-19 by gathering information from patients such as X-ray images, temperature, breathing ventilation, sweat transition, and heart signals. The system classifies X-ray images and predicts the state of patients using three deep learning models, namely ResNet50, InceptionV3 and InceptionResNetV2. This study will help health workers manage and detect COVID-19 patients.

Artificial intelligence once an efficient technique has been applied in many medical fields as a fast predictive and efficient way of profiling many medical conditions related to brain surgery, pulmonary diseases, and cardiology[21]–[26]. Different AI models were employed to classify COVID-19 and non-COVID-19 x-ray and CT scan in which (81.5% – 95.2%) and (95.4% – 100%) were achieved in CT scan and x-ray scan respectively[27]. CovXNet was employed to classify xray images of normal, COVID, viral, and bacterial types of pneumonia, the classification on the four classes achieved the highest accuracy of 90%[28]. [29] employ transfer learning through the Resnet50 pre-trained model, in retraining 41 epoch was adopted and an accuracy of 96.3% was achieved on all classes. RT PCR results were compared with CT scan images in COVID-19 detection, the earlier RT PCR shows negative results while the CT scan results show positive, this shows the efficiency of adopting medical imaging in profiling COVID-19 as it can detect the virus at early stage[30]. Grey Level Size Zone Matrix (GLSZM) coupled with SVM was employed to to classify CT scan images of COVID-19 and non COVID-19 images, base on tuning hyperparemeter validation fold 2, 5,10, the 10 fold achieve the highest accuracy of 99.68 [31].classification of pneumonia, covid 19 and non relevant to pneumonia or covid 19 was performed on CT scan images, the motivation of their work is to find an alternattive to RT PCR, and the highest ccuracy score was 86.7 %[32]. [33] compare two deep learning models, ResNet50 and Generative Adversarial Network(GAN), the training was performed on [34] dataset, the performance on the model was compared based on training set with augmentation and without augmentation, the best performing model was ResNet50 with accuracy=92.9, specificty =0.871 and sensitivity=0.778.

1.2. Contributions

The motivation in this study is to find a way to reduce the spread of the deadly COVID-19 and to detect COVID-19 at an early stage, the presently adopted benchmark COVID-19 testing method by WHO is the RT PCR, the RT PCR is costly as not all people in the world can easily have access to the test as most countries in the world economies are not good, most especially the third world countries. Proposing an accessible method of detecting COVID-19 is very important, that is why we looked at the most options used in screening COVID-19 positive patients, CT scans images can serve as a fast and efficient method compared to RT PCR and with few radiologist numbers in the world, the best alternative is to employ efficient Artificial Intelligence models. Our contributions in this work are:

(i) Three pre-trained deep learning models ResNet-50, ResNet-101, and VGG16 were proposed to classify COVID-19 and non-COVID-19 CT scan images.

(ii) AdaBoost Ensemble Classifier was introduced as a classifier to the pre-trained models which Serves as feature extractors.

(iii) The performance of the models based on the two classifiers Softmax and AdaBoost Ensemble Classifier was compared.

(iv) The best performing model outperformed the state of the art models employed on the same dataset.

2. COVID-19 Detection.

This section explains the features of the dataset used and the proposed pre-trained deep learning models for the identification of COVID-19.

2.1. Dataset

In this study, the dataset from [34] contains 349 COVID-19 positive images, and 397 non-COVID19 images were used for the training of different deep learning networks, 80% of the data was used for training, and 20% of the data was used for testing. Samples of COVID-19 and Non-COVID19 CT scan images are presented in fig.1. and fig.2. respectively.

Fig 1. COVID-19 CT image.

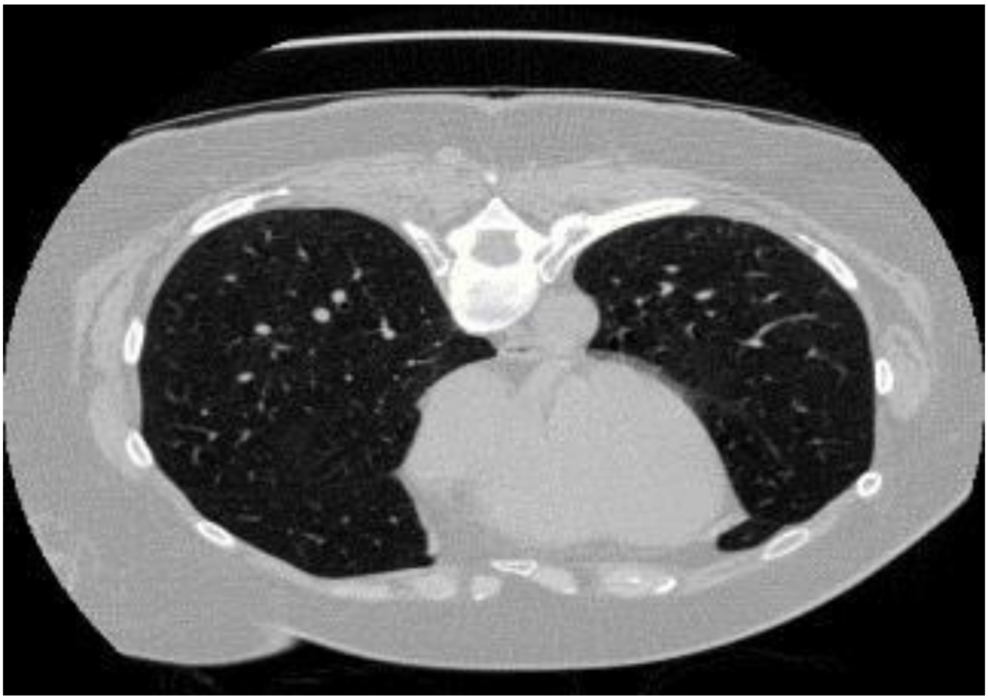

Fig 2. Non-COVID-19 CT image.

2.2. **Transfer Learning**

Transfer learning is a research problem in machine learning that centres to preserve the knowledge learned while solving a problem and applying it to another, but a related problem. Transfer learning can be achieved by retraining the fully connected layers of pre-trained models and freezing the extraction features such as filters and other parameters. [22], [28], [35]–[37].

2.3. **ResNet**

ResNet is a deep learning algorithm used in classifying images. The key concept behind ResNet is to deal with disappearing gradients that degrade network output induced by piling up a convolution layer over a pooling layer in deep network architecture, shortcuts that include identity is a residual block, the idea of inserting skip connections effectively removes a high training error, other deep networks do not contain an identity connection. That is why ResNet is different, ResNet-50 contains 50 layers and ResNet-101 contains 101 layers.

2.4. **VGG16**

VGG16 is a deep learning model that contains 16 layers, out of the 16 layers 5 are convolutional layers, 3 trainable layers, and the remaining layers are max-pooling layers. This architecture was the 1st runner up of the Visual Recognition Challenge of 2014 i.e. ***ILSVRC-2014***

2.5. **AdaBoost Ensemble Classifier**

AdaBoost is an ensemble strategy that trains and sequentially adopts trees. AdaBoost implements boosting where a group of weak classifiers is associated in sequence such that each weak classifier can increase the classification of samples misclassified by the previous weak classifier. In this way, the fusion of weak classifiers would be improved in sequence to create a strong classifier. Decision trees used in boosting approaches are referred to as "stump" since each decision tree appears to be shallow constructs that are not over-fitting but may be biased. The real tree is taught to pay particular attention to the absence of the previous decision tree. The weight of the sample misclassified by the preceding tree will be raised so that the next tree will work on the correct classification of the previously misclassified specimen. Classification precision improves with the inclusion of weaker classifiers to the model in sequence, although this can lead to unnecessary over-fitting and a decrease in generalization capabilities. AdaBoost is suited for imbalanced datasets but does not perform well in the presence of noise. The AdaBoost hyperparameter optimization is much more complex than the RF classifier.

3. Preprocessing and Training

3.1. Preprocessing

Data preprocessing in deep learning is the process of perfecting data in such a way that it can fit the input of a network and increase the number of datasets for robust and better training. There are several types of data preprocessing such as resizing, augmentation, and smoothing in training medical images. In this study, to improve the robustness of the deep-learning network training and increase the number of training data, data augmentation was performed on the training set data, these augmentation methods are random reflection, random translation along the x-axis, random translation along the y-axis, random rotation and flip[25], [33].

3.2. Training

In this study, three pre-trained deep learning models were employed namely ResNet-50, ResNet101[38], and VGG16[39]. Two types of training were performed to determine the models with the best performance.

(i) Employing transfer learning using the pre-trained networks for feature extraction and classification

(ii) Employing transfer learning using the pre-trained networks for feature extraction and AdaBoost Ensemble Classifier for classification.

In the first set of training two CT scan images of COVID-19 and Non-COVID-19 classes were classified by fine-tuning the pre-trained networks hyperparameters Epoch=20, validation fold=3, Mini batch size =20, and learning rate = 0.0001. the whole network structure was used. The batch size determines the stability of training, to reduce error generalization small batch sizes are adopted in most training though they are noisy, they offer regularization and also make it easier to fit one batch size on GPU [40]. while in the second training features were extracted using the pre-trained models' layers from the input layer up to the last pooling layer, the fully connected layers and the softmax classifier are replaced by the AdaBoost Ensemble classifier. The process of the training is presented in fig.3.

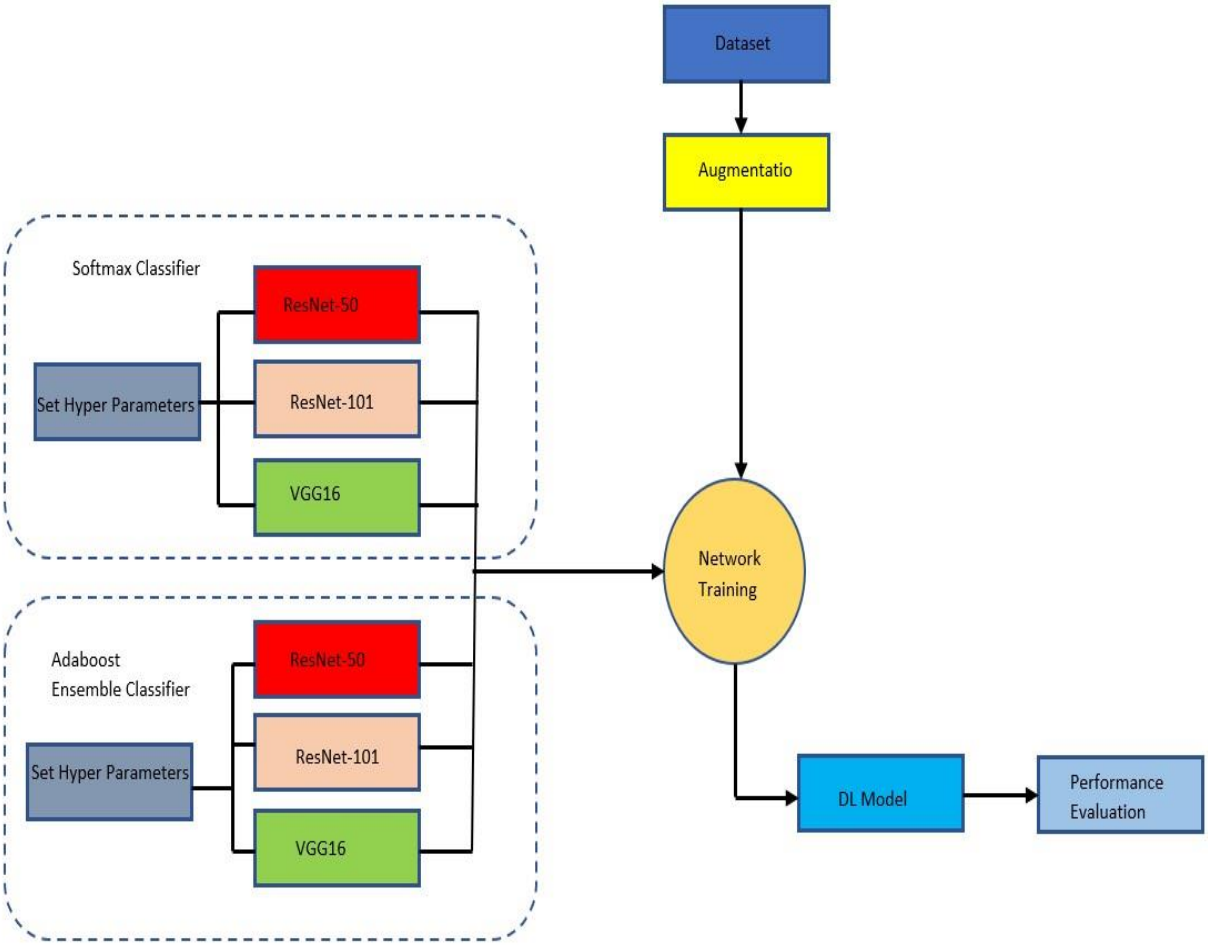

Fig.3. Training process

Results and Discussion

In this study, we improved the state of the art models employed on the dataset [34] by employing transfer learning, data augmentation and changing the architecture of the pre-trained models by applying AdaBoost Ensemble Classifier, the three different pre-trained network ResNet50, ResNet101, and VGG16 models were trained and compared with the state of the art model.

In table 1, base on the three models ResNet50, ResNet101 and VGG16. ResNet50 achieved validation accuracy=87.5%, sensitivity=0.83, specificity=0.82, precision=0.99, F1-score=0.95, Yonden Index=0.78 and AUC=0.92. ResNet101 achieve a validation accuracy=85.71, sensitivity=0.83, specificity=0.87. F1-score=0.91, precision=0.99, Yonden index=0.91and AUC=0.81. for the VGG16 accuracy=74.9, sensitivity=0.89, specificity=0.63. F1-score=0.94, precision=0.88 , Yonden index=0.52 and AUC=0.76. ResNet-50 with AdaBoost Ensesemble classifier achieves an accuracy of 97.33, sensitivity of 0.92, specificity of 0.95, F1 score of 0.94, Precision of 0.935, Yonden Index of 0.94 and AUC of 0.989. the ResNet-101 with AdaBoost Ensesemble classifier achieves an accuracy of 85.3, sensitivity of 0.857, specificity of 0.850, F1 score of 0.845, Precision of 0.833, Yonden Index of 0.707 and AUC of 0.854, while the third models VGG16 with AdaBoost Ensesemble classifier achieves an accuracy of 78.7, sensitivity of 0.80, specificity of 0.775, F1 score of 0.778, Precision of 0.757, Yonden Index of 0.575 and AUC of 0.788.

Table 1. Comparison of models performance with state of the art models.

Ref.	Models	ACC(%)	SN	SP	F1-Score	PR	YI	AUC
	ResNet-50	76.3	0.659	0.763				
	ResNet-50+augmentation	82.1	0.776	0.876				
	GAN	73.3	0.8	0.943				
[33]	GAN+augmentation	81.4	0.617	0.819				
	VGG16	76			0.76			0.82
	ResNet18	74			0.73			0.82
	ResNet-50	80			0.81			0.88
	DensNet121	79			0.79			0.88
	DensNet169	83			0.81			0.87
	EfficientNet-b0	77			0.78			0.89
[41]	EfficientNet-b1	70			0.79			0.84
	ResNet50	87.5	0.83	0.82	0.99	0.95	0.78	0.92
	ResNet101	85.71	0.83	0.87	0.99	0.91	0.91	0.81
	VGG16	74.9	0.89	0.63	0.88	0.94	0.52	0.76
	ResNet50+AdaBoost	97.33	0.928	0.950	0.94	0.935	0.94	0.989
	ResNet101+AdaBoost	85.3	0.857	0.850	0.845	0.833	0.707	0.854
Ours	VGG16+ AdaBoost	78.7	0.800	0.775	0.778	0.757	0.575	0.788

While comparing the performance of the proposed models, it was observed in fig.4 and fig.5 that the model which achieves the highest accuracy and specificity was ResNet-50 with AdaBoost ensemble classifier, as presented in fig.6 and fig.7, this shows that the combination of pre-trained deep leap learning model as feature extractor and AdaBoost ensemble classifier can improve the detection of COVID-19, this combination also outperformed the sate of the art models used in classifying COVID-19 and non-COVID-19 CT scan images of the same dataset used in this study. Finding a very efficient and cost-effective way of detecting COVID-19 is very important, an alternative to RT PCR is looking towards medical imagine most especially for pregnant women and children who are not supposed to be exposed to radiation[10], [11]. The study [12][10] shows the capability of medical imaging, in this work, we compare the performance of trained models on CT images and achieve very efficient models that can detect COVID-19, as the deadly COVID19 is declared as world pandemic, low cost and accessible method of detecting the virus at an early stage is very important considering countries with poor health facility and poor economy, though CT scan is a little bit expensive, the performance on the model shows a promising solution.

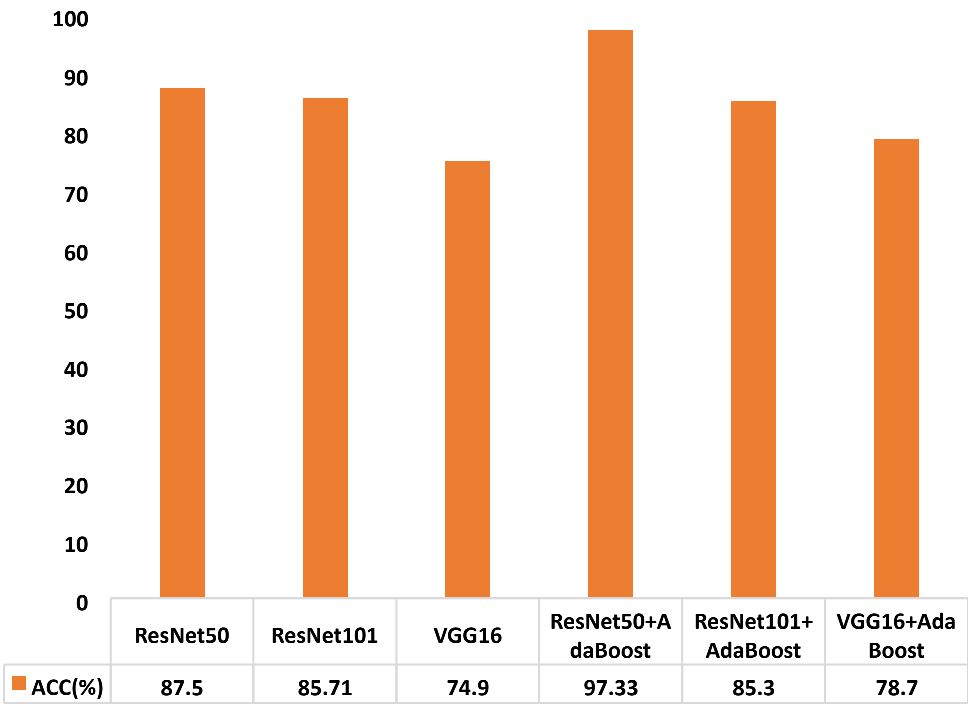

Fig.4. Proposed models accuracy comparison.

Fig.5. proposed models performance comparison.

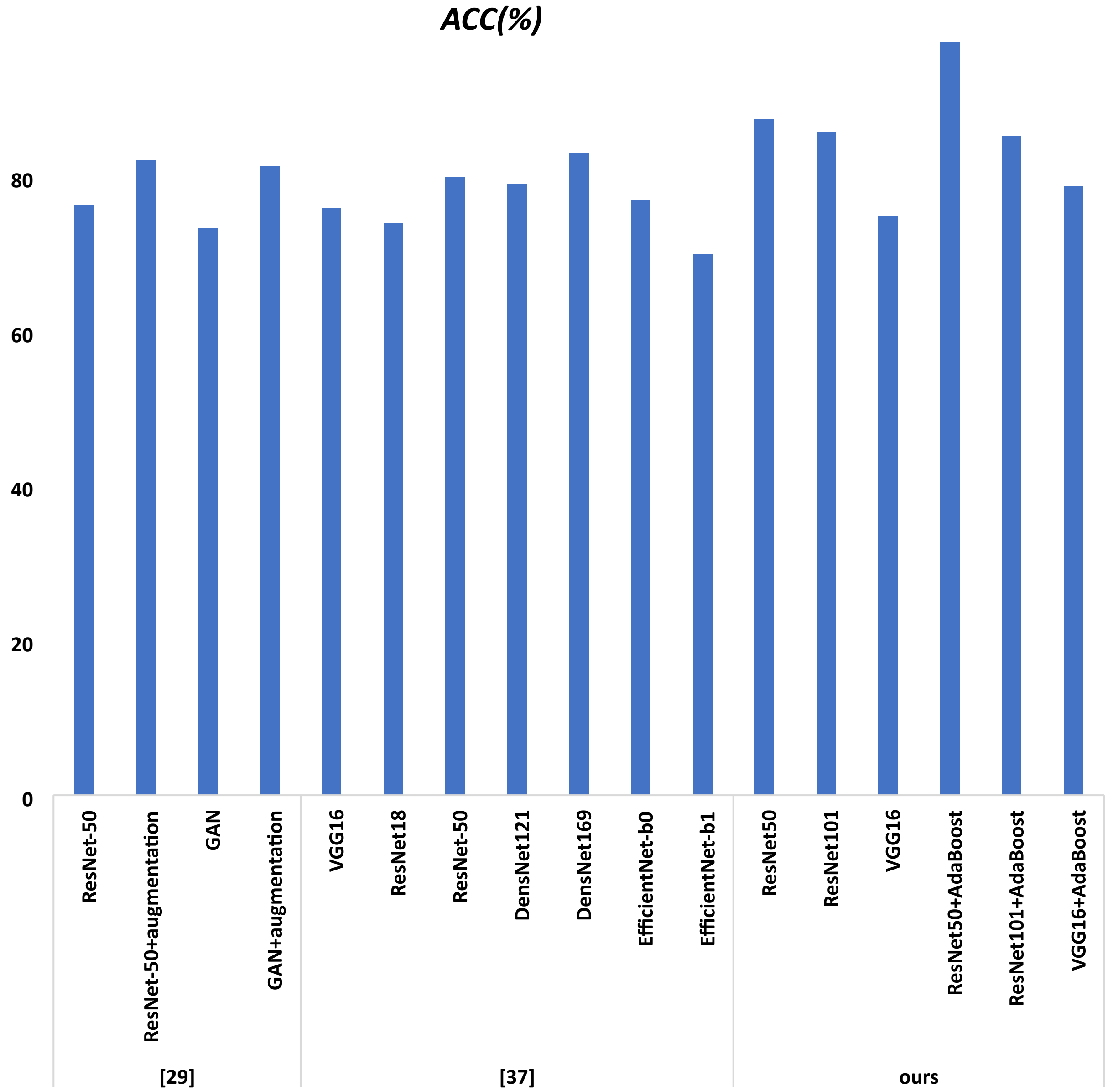

Fig.6. Proposed models accuracy compared with the state of the art models accuracy

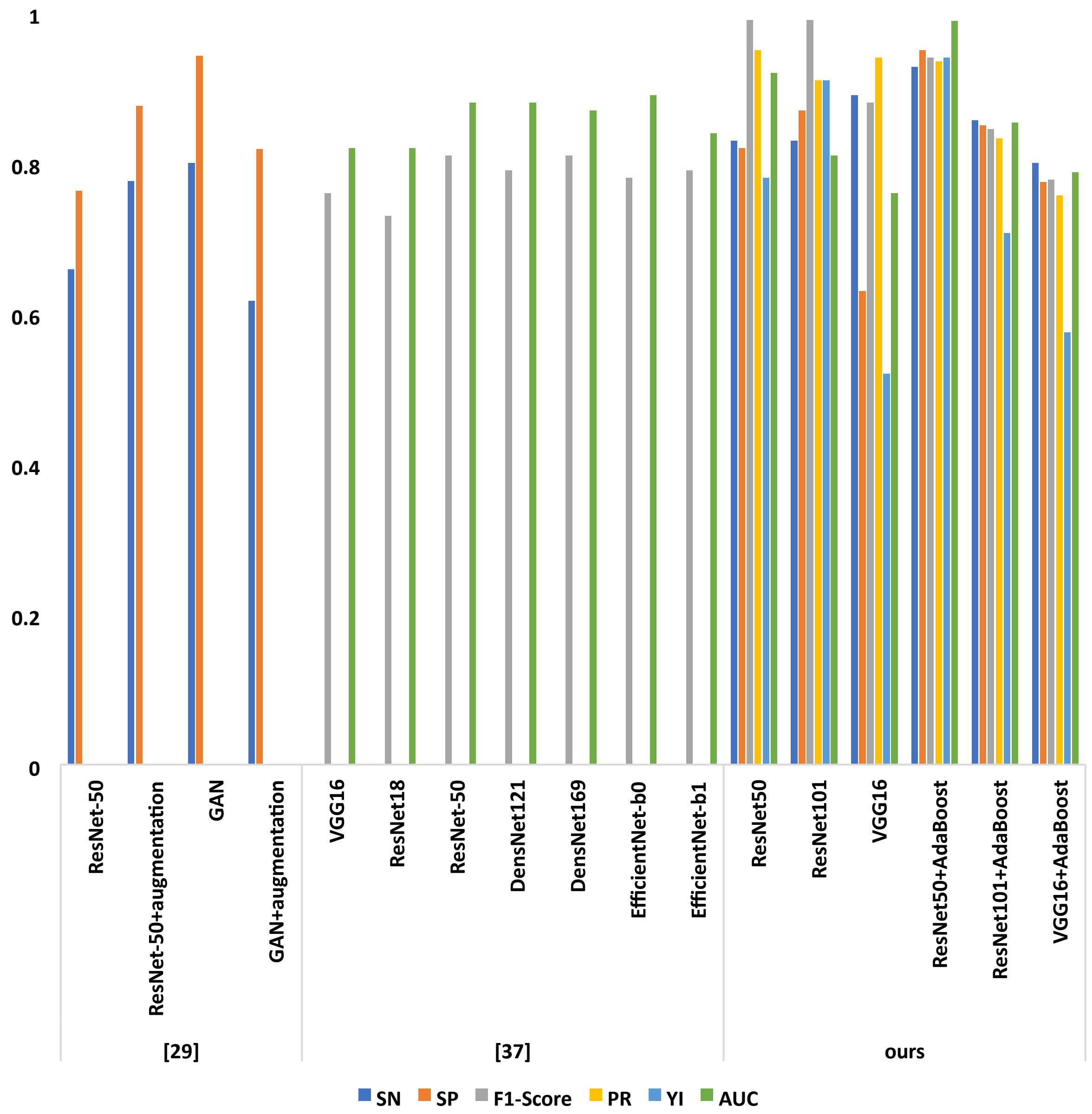

Fig.7. Proposed models performance compared with the state of the art models performance

Performance Criteria Accuracy

Accuracy is a measure that gives insight into how well the model learned and is producing a reliable result. It is the fraction of predictions that were provided correctly by the model. The accuracy of a model is the ratio of correctly predicted samples to the number of input samples. The number of correctly predicted samples is the sum of the number of true positives and false negatives

Accuracy = (TP+TN)/(TP+FP+FN+TN) *(1)*

Sensitivity or Recall

Is the ability of a model to test correctly and identify patients with a disease as Presented in equation (2).

Recall/sensitivity = TP/(TP+FN) *(2)*

Specificity

Specificity is a measure of how many negatives the trained model managed to capture out of the entire set of correctly predicted negative values by labelling the samples as negative. The relation for calculating specificity is presented in Equation 3.

Specificity = TN/(TN+FP) *(3)*

F1-Score

F1-score is a measure of the balance between the precision and recall of a model. It is used to perform a statistical analysis of the test accuracy. The F1-score of a model lies between 0 and 1. It is said to be very good if its value lies near one and very bad if it is near zero. It is calculated as given in equation 4

F1 Score = 2(Recall * Precision) / (Recall + Precision)* *(4)*

Yonden Index

Is the cut-point that optimizes the biomarker's distinguishing ability when equal weight is given to sensitivity and specificity, it also gives the summary of the receiver operating characteristic (ROC) curve. presented in equation 5.

Yonden Index=(sensitivity+specificity)-1 *(5)*

Precision

Precision is a measure of how precise or accurate the model is in terms of positive classifications. In other words, it measures the number of true positives out of all the predicted positives. The relation for precision is presented in Equation 6

Precision = TP/(TP+FP) *(6)*

Conclusion

In this study, we have achieved the classification of CT scan images by employing transfer learning with different classifiers using ResNet50, ResNet101, and VGG16 pre-trained networks, the performance achieved base on the performance criteria validation accuracy, sensitivity, and specificity, precision, F1-Score, AUC, and Yonden Index show how great the deep learning models can perform in COVID-19 detection using CT scan images. Base on the results on the best performing model ResNet50 with AdaBoost Ensemble Classifier, it shows that we achieved higher accuracy, sensitivity, specificity, precision, F1 score, Yonden Index, and AUC Compared to the state of the art models employed on the dataset. By adopting deep learning for COVID-19 detection using CT scan images, the method will help in profiling the patient's status very fast and efficiently. To reduce the spread of the virus as the virus incubation period is 14 days, though most of the patients show mild symptoms, before confirming their status they need to be isolated, which will come with cost penalty on the patient or the government, with early detection the patients can be put on medication at an early stage and recover on time and for pregnant and children the CT scan will be the best alternative.

Acknowledgement

This research focuses on those affected by the COVID-19 pandemic and those who are helping to fight this war in whatever way they can. We would also like to thank the doctors, nurses, and all healthcare providers who are putting their lives at risk in the fight against the coronavirus outbreak.

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ISSUES AND CHALLENGES ASSOCIATED WITH MACHINE LEARNING TOOLS FOR HEALTH CARE SYSTEM: A REVIEW

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ABSTRACT- The support of Artificial intelligence (AI) can be used to update traditional healthcare services, and it can efficiently serve society. Using machine learning tools, the diagnosis process can be automated, and practitioners can process large-scale clinical data to generate quick medical advisory for patients. This paper will analyze the contribution of machine learning tools in the medical domain. It will discuss prediction schemes for the healthcare industry, drug discovery, and human trials using machine learning and surgical operations with machine learning assistance, etc.

Keywords- Machine Learning, Health Care, Automated Diagnosis.

I. INTRODUCTION

Traditional healthcare services detect diseases basis on the patient's symptoms and recommend different treatments. All these processes produce a large scale of clinical data. Manual processing of this data is very complex and time-consuming, thus may delay the diagnosis process, and patients' health cannot be recovered timely. Artificial intelligence (AI) plays an essential role in processing this clinical data, and efficient results can be achieved in a timely manner. Following figure 1 shows the classification of clinical data:

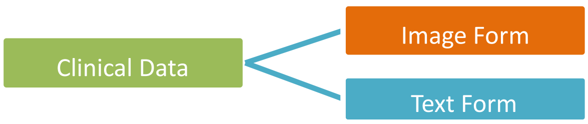

Figure 1. Classification of Clinical Data

The Image form of clinical data consists of the following:
(a) Medical Images: These images can be produced using different technologies as given below [37-42]:

Figure 2 CT scan of Lungs

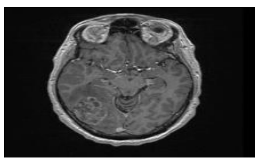

Figure 3 MRI scan of the Brain

Figure 2 shows the CT scan of the Lungs that is produced using multiple x-ray images with different angles/cross-sections. Figure 3 shows the Magnetic Resonance Imaging (MRI) scan of the Brain that is produced using radio waves and magnetic fields.

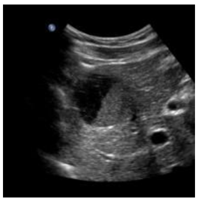

Figure 4 Ultrasound image of Lever

Figure 5 X-ray of Chest

Figure 4 shows the ultrasound image of Lever that is produced using high-frequency sound waves. Figure 5 shows the X-ray image of the chest that is produced using ionization radiation.

Figure 6 Nuclear medicine of Heart

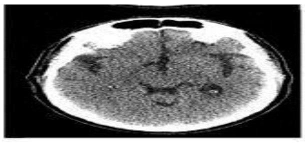

Figure 7 Positron-Emission Tomography of Brain

Figure 6 shows the Nuclear medicine image of the Heart that is produced using radioactive tracers. Figure 7 shows the Positron- Emission Tomography image of the Brain that is produced using radionuclides. As per requirements, the practitioner refers the scan type to each patient. The Text form of clinical data consists of the following:

- Meta Data: Lab test report, patient personal information, current health status, medical history, feedback, disease, diagnosis and treatment details, etc.

Above discussed data is used to build a complete medical record of patients, and AI can extract customized facts with the help of various machine learning algorithms. These facts may be used for:

- Prediction of disease and diagnosis through ○ Medical image processing ○ Clinical Text data mining
- Development of an automated decision support system
- Drug discovery and human trials
- Surgical operations using robotics

Following figure 8 shows the various approaches that can be adapted for machine learning to achieve the above-discussed points:

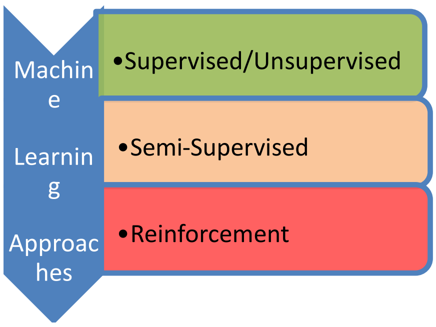

Figure 8. Machine learning Approaches

In the case of supervised learning, input datasets are used for training, whereas in unsupervised learning, labeled datasets are used for semi-supervised learning. Reinforcement learning uses feedback values to refine the output [1-5]. The sections below explore the contribution of various researchers for the different stakeholders (practitioners/patients).

II. MACHINE LEARNING-BASED PREDICTION SCHEMES FOR THE HEALTHCARE INDUSTRY

Using clinical data, training datasets can be developed, and estimation of current disease stage and health status can be determined using machine learning algorithms that can enhance the proficiency in disease detection and diagnosis process. The following section describes the machine learning-based prediction for healthcare services:

M. D. Samad et al. [6] explored machine learning-based methods that can predict survival accuracy using limited input variables for echocardiography outcomes. The study found that traditional methods use Ejection Fraction and Comorbidities based prediction models, which are less accurate than the machine learning algorithms.

Y. Xue et al. [7] developed a prediction model for patient readmission and compared its performance to the Support Vector Machine/Random Tree based methods. Analytical results indicate that Functional Independence Measure method outperforms traditional methods. Training and validation were performed using existing clinical data, and accuracy and sensitivity were adjusted by finding the optimal cutoff point of the receiver operating characteristic curve. Results state that it can reduce the overall treatment cost as well as it can also improve the quality of healthcare services. A. Clim et al. [8] investigated the relationship between chest sounds and the level of hypertension. They found that a prediction scheme based on KullbackLeibler Divergence is more accurate and can enhance clinical decision support compared to traditional methods. C. R. Olsen et al. [9] investigated machine learning algorithms' role in diagnosing heart diseases. The study indicates that these methods can assist the practitioners for diagnosis and can also be used to develop the prediction models per the patient's classification. Integrating these algorithms with the BigData framework can also analyze large-scale disease datasets.

F. Y. Qin et al. [10] developed a predation framework for the health analysis of elderly patients. It builds the predicates by perfuming the feature classification. Finally, a dataset is used for training and validation purposes. Experimental results show that it outperforms in terms of prediction accuracy as compared to traditional schemes (Artificial Neural Network/Super Vector Machine). X. Du et al. [11] developed a perdition model for detecting cancer symptoms in earlystage patients. It uses both linear/non-linear models to process the input parameters, and analysis shows that the proposed scheme outperforms in terms of various parameters, i.e., sensitivity/ Specificity /F1-Score/ Precision/ Recall/ROC Curoff, etc., as compared to traditional methods. Y. Wang [12] et al. developed a scheme to predict the probability of mental disorders after brain surgery. After calculating the risk factors associated with the patients, practitioners can adapt the appropriate therapy/drugs/treatment to reduce the risk of such disorders. The proposed scheme was analyzed using different algorithms (Decision Tree/Regression/Random Forest/Gradient Boosting) under the constraints of various parameters (sensitivity/ Specificity /F1-Score/ Precision/ Recall/ROC Curoff etc.). Experimental results indicate that higher risk factors of mental disorders can be reduced with the help of machine learning algorithms.

K. N. Qureshi et al. [13] utilized a mobile platform to collect the patient data that can be used to forecast heart disease. Compared to existing methods (Neural Network/ Support Vector Machine/Native Bayes), it outperforms in terms of optimal accuracy/sensitivity/specificity. It can be further extended to analyze the impact of various Brain-related injuries on human beings. A. Akbulut et al. [14] developed a prediction scheme that utilizes the clinical datasets to predict anomaly status using different binary classification models. Experimental results show that the decision tree-based model is more accurate than another state-of-the-art model. It can be further migrated to the mobile platform to analyze large-scale datasets. K. N. Kunze et al. [15] developed a random forest approach to predict patient dissatisfaction after knee surgery. It considers various facts, i.e., age, allergy to medicines, etc., as input for the prediction chart. Experimental results indicate that risks related to health and dissatisfaction level can be accurately predicted, and patients' health status can be optimized using feedback. However, the lack of data validation is still an open issue. It can be resolved in the future. A. Talukder et al. [16] used different machine learning algorithms (logistic regression/linear discriminant analysis/support vector machines/k-nearest neighbors /random forest) to predict the malnutrition level in children. Countrywide data was collected and used for perdition purposes. Analysis shows that random forest outperforms higher specificity/accuracy/ sensitivity compared to other methods. This study can be further used to manage malnutrition, identify the associated health risk, improve healthcare services, etc.

III. Automated Decision support system

In the case of the primary healthcare system, practitioners manually examine the clinical data that may be error-prone, and its processing is quite complex and time-consuming. All these factors degrade the efficiency of decision-making and affect the diagnosis process. The traditional process of medical data examination for decision-making can be altered using machine learning algorithms. The section below discusses the contribution of the researchers in this area.

H. Yin et al. [17] developed a framework that collects data from wearable sensors and computedassisted medical systems. A machine learning-based scheme is used to process and classify the patients as per disease categories. Output data is further used for decision-making and diagnosis purpose. Experimental results show that it can improve treatment accuracy, and practitioners can utilize multiple datasets to improve healthcare services. S. Anakal et al. [18] introduced a decision support system to diagnose chronicle lung diseases. It uses different machine learning schemes, i.e., Decision trees/Support vector machines/neural networks/ Classifier Ensembles, etc. Experimental results show that practitioners can redefine their treatment strategies and utilize the system feedback to manage patient drug levels. It can be integrated with a cloud platform to provide telemedicine support for remote areas.

A. P. Eremeev et al. [19] analyzed for decision-making to process the medical data at a large scale that may be available in images or text form. It is also quite complex to store and corelate the facts in this data. Study shows that NoSql databases are more suitable to store this type of dataset and supports optimal response time for query execution, and can be easily integrated with machine learning tools as compared to traditional databases. K. Shailaja et al. [20] studied various machine learning methods that can be used for the diagnosis and decision support of various diseases (heart/diabetes /cancer). Analysis shows that different schemes have different accuracy level for each type of disease, i.e., native bays has the highest accuracy level for diseases related to the Heart. In contrast, classification and regression-based methods provide more accurate results for diabetic patients and cancer patients; support vector machine provides the highest prediction accuracy. The analytical data of this study can be utilized further to improve the accuracy level of other machine-learning tools.

H. R. Mansilla et al. [21] presented a decision support framework that can analyze the risk of infection after surgery. Practitioners can use the alternative treatment type to avoid these side effects. It uses the combination of a support vector machine and a decision tree to balance the accuracy level in results. Experimental outcomes show that estimating infection risk can optimize the diagnosis strategies. A. Yahyaoui et al. [22] developed a decision-support framework for diabetic patients that use a deep learning approach for disease prediction and diagnosis support. Experimental results show its performance in terms of prediction accuracy compared to traditional approaches (Random Forest/Support vector machine). Its accuracy can be further enhanced by integrating deep feature extraction. C. Comito et al. [23] developed an automated decision support system that can assist the practitioners as per the available datasets built using different medical data resources (Lab test/patient health records). Experimental results show that deep learning can detect symptoms early, and diagnosis plans can be suggested for identified diseases. A. Triantafyllidis et al. [24] explored the integration of machine learning schemes with electronic health records and decision support systems to predict and manage childhood obesity. Analysis shows that prediction accuracy can be achieved using decision trees/neural networks, and effective treatment plans can be designed to prevent obesity at early stages. The analytical data of this study can be used for mobile diagnosis platforms. W. O. N.d. Hollosy et al. [25] used supervised learning methods (Decision Tree/Boosted Tree/Random Forest) to develop a decision support framework to diagnose patients with low back pain. Analysis shows that few parameters vary during testing and data validation (accuracy/ sensitivity/ precision/ specificity). However, the overall time of the diagnosis process can be reduced using this framework, and it can be integrated with large-scale global datasets. N. P. Smadja et al. [26] investigated the support of machine learning methods for the decision support system. The study found that the performance of these schemes depends on the input datasets having limited facts about symptoms. For each disease type, the accuracy of decision-making may differ.

IV. Drug discovery and human trials using machine learning

Drug development is quite a complex and time-consuming process and directly relates to the type of disease, symptom, dose, intake frequency, etc. All these factors play an essential role in human drug trials, as new drugs may have some side effects on the human body. There is a need to recognize the risk factors associated with its development process and reactions to patient's health/ disease etc. Machine learning offers an automated platform for drug development and trial. The section given below explores the solutions developed by other researchers in the relevant domain:

L. Zhao et al. [27] investigated the challenges associated with pharmaceutical research and drug development. The study found few facts (data source/ quality/ format/ validity/authenticity/data rate/ volume/ values) directly influencing drug development cost. Large-scale data related to the drug can be analyzed through the integration of machine learning/deep learning algorithms over big data platforms, thus reducing the overall R&D cost of drugs. C. Réda et al. [28] surveyed the association of diseases with different drugs and their impact on the drug development process. Analysis shows that a complete knowledgebase of diseases can be acquired using machine learning algorithms and it may reduce the research cost as well as its human trials may be conducted at earlier stages and feedback from number of successful trials can be utilized to refine the drug modeling process/dose/accuracy level etc. R. Ietswaart et al. [29] developed a random forest approach based model to find out the association of drug reactions over patients. Several drugs was used for training purpose. Its performance was verified using different parameters (accuracy/correlation coefficient/recall curve/ precision etc.). Outcomes show that large-scale analysis of drug reaction associations can optimize the failure rate of drug trials. Machine learning also provides a platform for random experiments, and no human/animal is required. N. T. Issa et al. [30] explored the drug development issues related to cancer/tumor. They found that drug repurposing strategies can be defined using existing largescale cell datasets to diagnose this disease, and drug development costs can be optimized. Analysis shows that training datasets can be updated using feedback to maintain experiments' accuracy. M. Ali et al. [31] investigated several machine learning approaches to extract the cellrelated data from cancer patients and prepare training datasets for detection and diagnosis purposes. Analysis states that feature extraction of cells and drug response to patient's health can be used to predict the response of cancer drugs as well as these outcomes can also optimize the drug development cost.

V. Surgical operations with machine learning assistance

Surgery is a complicated operation through which patients may be recovered or not. Even after surgical operation, it may have the side effect over the patient health. So there is a need to investigate the risk and side effects of surgery on a patient's health. Machine learning algorithms can be utilized to overcome from these issues as described below:

L. Štěpánek et al. [32] investigated the role of machine learning in plastic surgery and multiple facial expression dataset was used to perform Multivariate linear regression using R language. Experimental results indicate that a neural network can achieve higher accuracy for facial geometry, and Bayesian naive classifiers/decision trees can be used to map the facial image to emotions. T. J. Loftus et al. [33] explored the risk associated with the surgical wards where the quick assessment of high-risk patients is essential, and error-prone diagnosis and treatment recommendations may lead to the failure of healthcare services. Using wearable sensors, real-time health analysis and electronic health records can be generated for such risks. The medical data can be further processed using machine learning techniques to recognize the symptoms at earlier stages and achieve higher accuracy. A. W. Schwartz et al. [34] studied virtual reality-based surgical operations and investigated their integration with machine learning schemes. The analysis found that combining both technologies can be utilized to develop a largescale knowledge base to help the stakeholders. L. Štěpánek et al. [35] analyzed facial feature extraction and their classification using a machine learning algorithm that can refine facial plastic surgery outcomes. Analytical data shows that geometry features, along with sufficient datasets as evidence both, can be enforced to maintain the quality of facial attractiveness. K. Merath et al. [36] analyzed the compilations associated with the different types of surgical operations (Liver/ pancreatic/ colorectal) and developed a solution to predict the complications using decision tree models. Experimental results show its performance in terms of higher prediction accuracy and efficient risk analysis related to diagnosis. Its scope can be enhanced using electronic health record system.

VI. SUMMARY TABLE

	Contribution
Section-I	This section introduced the concept and role of artificial intelligence
	based solutions for healthcare industry. It described the various sources of clinical data, its forms and the available machine learning based approaches etc.
Section-II	This section described about the various existing solutions that can be used for prediction of disease and its diagnosis purpose, patient's health status etc.

Section-III	This section discussed the automated decision support system and clinical data collection/processing based on machine learning approaches.
SectionIV	This section explored the complex stages of drug discovery, its trial over patients, and how machine learning algorithms can optimize this time-consuming process.
SectionV	This section investigated the side effects of surgery on patients' health, risks, machine learningassisted surgical operations, etc.

VII. CONCLUSION

This paper reviewed issues and challenges associated with the AI and machine learning tools. Various researchers recognized the potential of these tools and contributed their efforts to build the modern healthcare system. It includes various perdition models that can be used to predict readmission, hypertension, heart diseases/cancer symptoms, the health status of elderly patients' mental disorders, anomaly status, patient dissatisfaction after surgical operations, children's health care, and malnutrition level. Machine learning schemes can be integrated with traditional decision support systems, and practitioners can utilize the existing datasets as benchmarks for training, validation, and diagnosis. Machine learning algorithms can be used to identify the disease behavior of the patients as well as the reaction of drugs to the patient's health. Automated drug trials can reduce the overall drug development cost, and drug trials can be performed without using live entities (human/animal). Machine learning tools can also be used to assist surgeons during operations. These can also be used to analyze the side effects of these operations on patient health, and complications associated with different surgeries can be predicted in advance to minimize the risk level. Patient feedback can be used to refine the diagnosis process. In the future, a machine learning framework will be developed to improve healthcare services.

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ETHEREUM BLOCKCHAIN, AI, AND CLOUD STORAGE FOR MEDICAL REPORTS

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Abstract- This study explores the application of blockchain technology in developing a secure medical record sharing system for managing health data stored in the cloud. The aim of this paper is to collect, secure, and enable sharing of medical records using the Ethereum blockchain, ensuring confidentiality and integrity while enabling efficient exchange of medical information among healthcare professionals through patient-specific medical profiles. The paper discusses the unique features of e-health and reviews the integration of Artificial Intelligence (AI), cloud computing and blockchain technologies to enhance security in digital health. The synergistic relationship between these technologies is examined, highlighting their combined potential for smarter and more secure applications. The project utilized MetaMask, a digital wallet, to purchase and connect to the Ethereum blockchain for securing the health report links and cloud storage to store the reports themselves. Moreover, Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) models were used to predict Ethereum blockchain transaction prices which provide insight to the user on potential impacts of the system and market trends. The results show that the implementation of the technologies is effective in healthcare data management where there is enhancement in decision making and security issues.

Keywords: IoT, AI, Machine Learning, Cloud Computing

1. Introduction

The healthcare industry is ever evolving and growing rapidly, with a relevant increase in the amount of data being generated [1]. Patient medical information such as nuclear magnetic resonance image, prescriptions and pathological results are private data and contain all the information of a certain patient. Quality patient care can be attained by making use of this type of data. However, managing and securing this data is essential for the health organizations as it helps protect patients' privacy. The development of technologies the electronic medical records
(EMRs)[2], cloud computing and blockchain has shown enough promise enable patients' data security and privacy. However, further research and development are needed to fully integrate these technologies into the healthcare system and ensure their effectiveness in protecting patient information. It is crucial for healthcare organizations to prioritize the implementation of robust cybersecurity measures to safeguard patient data and prevent potential breaches.

Blockchain technology has gained significant attention in recent times for its potential applications in different industries such as the healthcare. It was originally developed for cryptocurrencies[3]. Data management in the healthcare industry has benefited from blockchain technology in increased security, data integrity and privacy. It is impossible to tamper or manipulate data that has been stored in a decentralized network of nodes[4]. This allows sensitive medical information such as patient records to be protected. One of the blockchain technologies which is Ethereum, allows patients to have control of their data and therefore more control over their healthcare decisions. Artificial intelligence (AI) is also transforming healthcare data management. From its definition[5], AI can be used analyze patient's data and identify trends and patterns that may be missed by human analysis which in turn gives accurate diagnoses and better treatment decisions. Through predictive models, AI can help to anticipate patient needs and deliver personalized care. Another technology that is revolutionizing the healthcare industry is cloud computing. It provides a storage platform which is secure and scalable[6] for storing large amounts of healthcare data that is easily accessible. Cloud storage reduces the risk of data loss and provides security measures to protect against unauthorized access or data breaches.

The aforementioned three technologies are poised to transform the future of healthcare data management. Patient outcomes can be improved, operations can be streamlined and costs can be reduced by leveraging these technologies. With Ethereum blockchain, medical records stored in the cloud can be shared securely with multiple providers which in turn reduce the need to duplicate tests or procedures. AI technology can then be implemented in the automation of the saving processes of the data. Creation of patient reports can be done online thanks to cloud computing. Despite the numerous benefits provided by these developing technologies, there are also unique obstacles that must be addressed. One key impediment is the smooth transmission of data across platforms. To facilitate successful communication between systems, existing data formats and protocols must be modified. Furthermore, as healthcare information becomes more available through digital means, worries about data privacy and security have grown. To address these issues, healthcare providers must prioritize the implementation of strong security measures to prevent data breaches and potential cyber-attacks. With that said, the fundamental goal of our project is to create a system that allows doctors to write reports online, deliver them to patients, and follow their progress effectively. We are also going to implement a machine learning model to predict the prices of the Ethereum which can in turn help the patient decide when to transact.

Previous studies

As stated in the proposal that the aim of the project is to use JavaScript to build a frontend view of the project, a cloud service provider to host the content of the site and Meta Mask to be able to login to a user's wallet to be able to store and fetch the medical records. In order to get an in depth understanding on the project, a literature study on the topic was carried out. The following papers were reviewed:

In [7] proposed a decentralized application model that uses Ethereum private blockchain, InterPlanetary File System (IPFS) and associated web technologies to help healthcare providers, policymakers, and research organizations in Nepal. In their study, the authors used both quantitative and qualitative methods in gathering data from the citizens and medical doctor in Kathmandu, Nepal. A questionnaire of survey was given to 60 adults living in the city to learn how they archive their medical health records, their tendency in switching doctors and how medical history is presented. Interviews were also carried out from 8 medical doctors who gave an insight on their experience when dealing with patients without their medical history. The findings that were made were that there was asymmetry between doctors and patients regarding medical records. Patients can hardly remember their previous medical conditions and doctors did not have enough knowledge of patient's medical history. Therefore, the researchers proposed an application model which had a security layer, role-based access control and Ethereum private blockchain. The proposed application model aimed to create an accessible and informative medical record database for both doctors and patients while ensuring the security and privacy of patient data. The paper concludes that the proposed framework can provide effective healthcare services to patients by creating tamperproof and trustworthy patient data for health. The authors suggest that their research will play a meaningful role for future researchers in the field of healthcare and Blockchain technology. [8] proposed a system that combines blockchain and artificial intelligence to improve the accessibility and affordability of healthcare services. It utilizes a web application with image classification algorithms to detect diseases and charges a small fee in the form of a specially created cryptocurrency. This global digital currency operates on the blockchain and eliminates intermediaries, making healthcare diagnoses more cost-effective. The system optimizes clinical life cycle management and enhances clinical trial workflows, leading to faster insights and decision-making for patient care. The system aims to address both the speed and economic aspects of healthcare, providing efficient and affordable solutions through the integration of blockchain and AI technologies.

In another research, Mancer et al. [9] aimed to manage health data by collecting, storing and sharing electronic medical records using blockchain. The system that was proposed was designed to be decentralized, meaning that the data cannot be erased making it secured and non-tamper. Blockchain technology was used for the system in providing patients with proof and certainty that their medical records cannot be modified. The entity that was presented in this study was Secure Shared Medical Record (SSMR), which interact to provide control and data protection in the exchange of health information. The system provides doctors with medical information from other doctors, such as medical history, laboratory results, imaging, and treatment in progress. The paper concluded that blockchain technology has the potential to revolutionize several sectors, including healthcare. The proposed Secure Shared Medical Record (SSMR) system provides a secure and efficient way for doctors to access patient medical records from other healthcare professionals.

In another paper, [10] a blockchain-enabled emergency detection system for mobile healthcare was presented. It utilizes encrypted physiological information and smart contracts to detect emergencies without compromising patient privacy. The system improves security, trustworthiness, and communication resilience through blockchain technology. The authors provide a proof of concept and experimental evaluation, showing promising results. Their research offers a valuable contribution to the field of mobile healthcare by leveraging blockchain for secure and efficient emergency detection. Moreover, [11] highlighted the use of AI in healthcare, particularly in radiology, and its successful applications during the Covid-19 pandemic. It proposes the combination of blockchain and federated learning as a solution to maintain data integrity and privacy while improving AI models. The paper provides an overview of related work, presents the proposed framework, and concludes with future directions. It offers valuable insights into leveraging AI, blockchain, and federated learning for real-time healthcare needs.

The research conducted by [12] introduced a cloud-based implementation of blockchain security in the context of the Internet of Things (IoT). The study proposed a three-tier architectural framework that utilized pseudonym-based encryption, with a private blockchain deployed at the edge. The framework ensured that IoT devices had to authenticate through a gateway device before transmitting data to the cloud. Additionally, a public blockchain was implemented in the cloud, enabling a community of users to securely access the Electronic Health Record (EHR) system. [13] proposed a decentralized system using blockchain technology to store patient records, addressing the challenge of fragmented medical data. The system architecture involves a DAPP interface for patients and healthcare providers, granting access to comprehensive medical records. The use of blockchain ensures data security and accessibility. The system leverages Ethereum and IPFS for data storage and sharing, with a user-friendly DAPP interface. AI and ML techniques enhance the system's capabilities. Furthermore, the proposed architecture enables the availability of up-to-date and accurate medical data for training machine learning and deep learning models, enhancing their performance and prediction accuracy. The paper presents a promising approach for leveraging blockchain and machine learning in the healthcare industry

Methodology

Currently, patients' records are locked in multiple centralized systems which are maintained by different healthcare institutions. This means that the comprehensive medical data history of the patient has been locked away, making it difficult for doctors to make informed decisions. Using a decentralized system to store the patient record solves this issue. Figure. 1 shows the architecture of our proposed system.

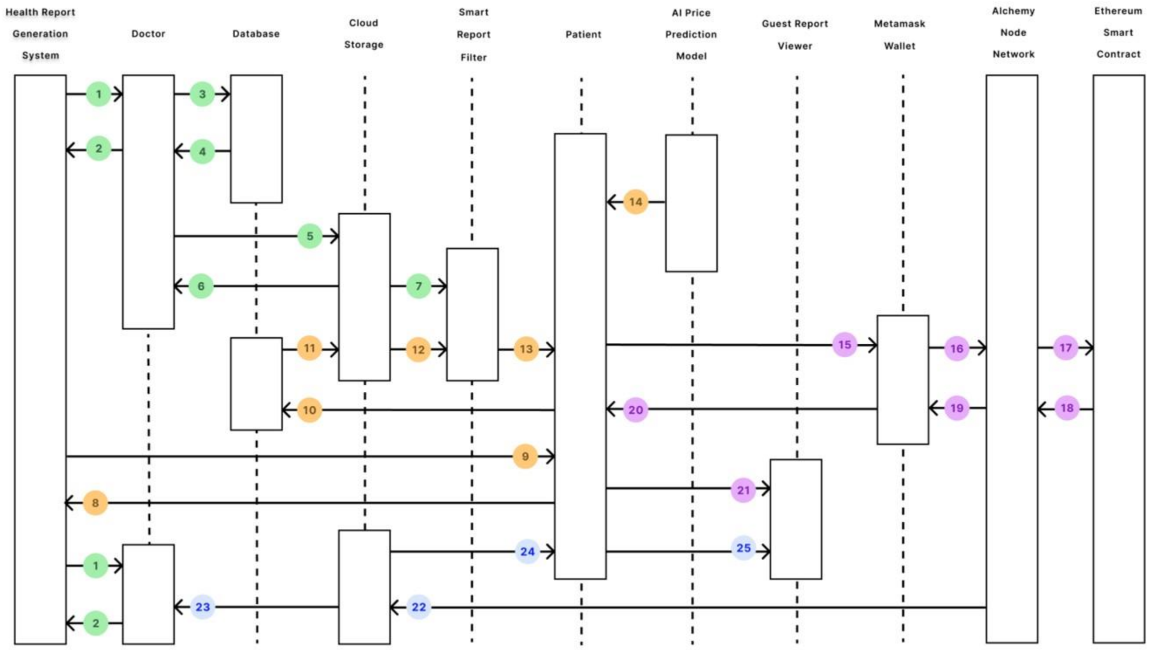

Figure 1. General Architecture of The Proposed System

The following list describes the arrows in the general architecture of our proposed system:

1. The doctor logs in.
2. The system authenticates the doctor.
3. The doctor dashboard fetches required data from the database.
4. Data is returned to the dashboard.
5. The doctor creates a new report and requests to store it onto the cloud.
6. The cloud storage stores the new report onto the cloud.
7. The smart filter ensures the report will go to the correct patient.
8. The patient logs in.
9. The system authenticates the patient.
10. The patient dashboard requests data from the database.
11. A request is sent to the cloud storage for the reports.
12. The smart report filter, filters the report for that patient.

13. Request is satisfied. The patient can see new reports from their doctors.
14. The AI Prediction Model sends predicted transaction prices.
15. The patient connects to the Metamask wallet.
16. A request is sent to an intermediary node network manager.
17. The addReport function runs on the Ethereum Contract.
18. A success message is returned.
19. The intermediary node network manager forwards the message.
20. The message reaches the user's dashboard.
21. A report link is generated for the guest report viewer.
22. Metadata is fetched from the Node Chain
23. Reports on the chain can be seen by the doctor who created the report
24. Reports on the chain can be seen by the patient who added the report to the blockchain.
25. Reports shared to a 3rd viewer can be seen on the guest viewer using a report link

The authors first built the User Interface (UI), which includes the login page for the doctor and the patient. We then have a page for the doctor to create a report for a certain patient. A dashboard is also available for the patient to review a report sent by their doctor, to approve it before adding it to the blockchain. Finally, a view is available for a guest who has been granted permission to view a report.

Figure 2. The Dashboard for The Doctor.

The next steps are to build out the logic when a doctor is creating a report, building the report templates themselves and being able to realize what kind of data those reports include by creating forms that the doctor can use to enter relevant data about the patient's health. In this project we focused on 2 types of diseases, High Blood Pressure and Covid-19.

Figure 3. High Blood Pressure Report Form.

Figure 4. Covid 19 Report Form

We fetch data using AJAX for the doctor about the patient details using their name and then write that data into the report form fields to make data entry quicker for the doctor. This also ensures that zero errors are made when entering personal details about the patient. Once the doctor creates the report. It is bound as a PDF file and then upload securely onto the cloud storage. The data must live somewhere. Within the MYSQL database, we have a reports table to be able to handle the movement of report metadata while it's in the doctor's view until he/she forwards it to the patient. The system includes smart filters that are there to filter reports from the doctor to the correct patient once it has been forwarded. Once the report has been created and forwarded, the patient can log in to their dashboard to review it. Here he/she will find the reports that have been forwarded by their doctors as well as a price prediction widget that will let them know the current transaction price, as well as the best time to upload their reports for the ceapest price.

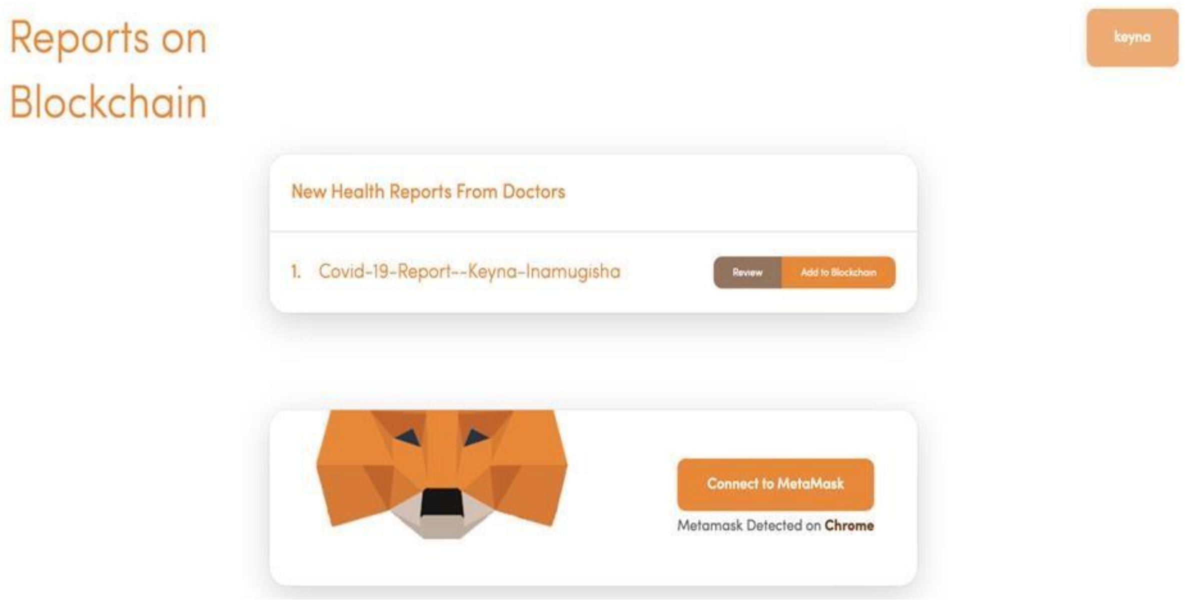

Figure 5. Patient Dashboard Page.

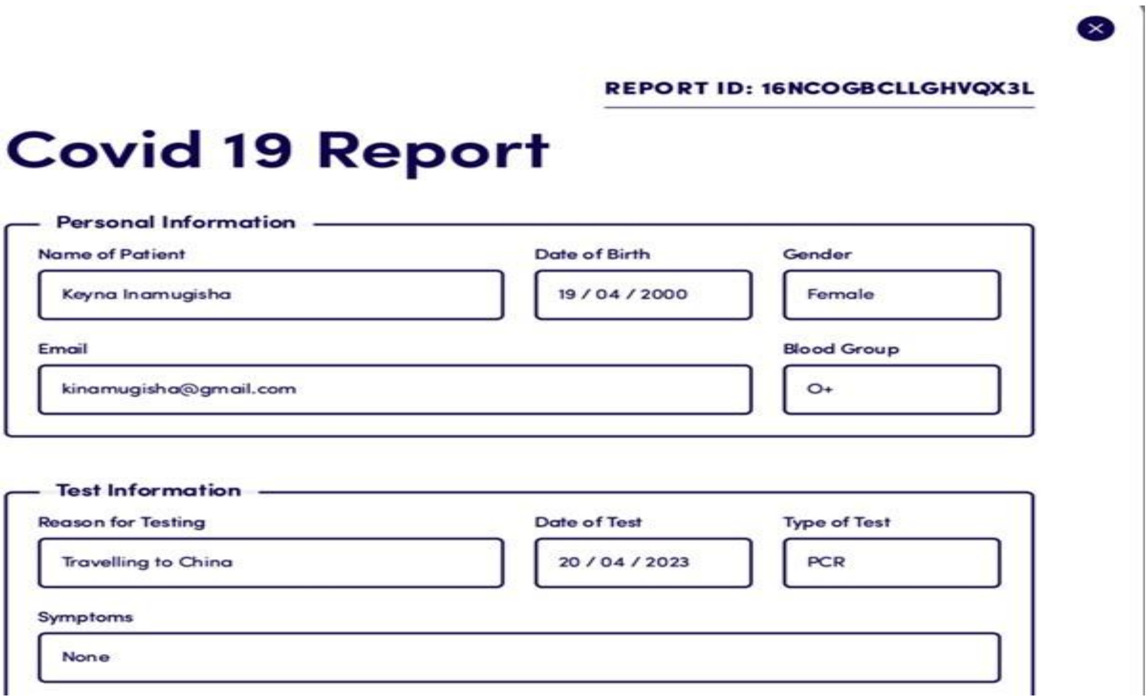

Figure 6. Reviewing Generated Health Report.

The price prediction feature was built using an RNN layered with LSTM nodes to build a time series forecasting model that is able to predict future transaction prices for Ethereum. The data includes transaction prices from dates ranging from *2020 to 2023*. The model was trained over 10 Epochs resulting is a very low loss value and a high accuracy value that was calculated by comparing the predicted values with the real values over a duration of seven days.

```
============================
--------------------------------------------------------------------------------------------
Layer (type)               Input Shape            Output shape          Param #
============================================================================================
dense_Dense1 (Dense)       [[null,4]]             [null,64]             320
--------------------------------------------------------------------------------------------
reshape_Reshape1 (Reshape) [[null,64]]            [null,16,4]           0
--------------------------------------------------------------------------------------------
rnn_RNN1 (RNN)             [[null,16,4]]          [null,16]             20352
--------------------------------------------------------------------------------------------
dense_Dense2 (Dense)       [[null,16]]            [null,1]              17
============================================================================================
Total params: 20689
Trainable params: 20689
Non-trainable params: 0
--------------------------------------------------------------------------------------------
```

Figure 7. Model summary of the RNN-LSTM model

```
const model = tf.sequential();

model.add(tf.layers.dense(
  {units: input_layer_neurons, inputShape: [input_layer_shape]}
  ));
model.add(tf.layers.reshape({targetShape: rnn_input_shape}));

let lstm_cells = [];
for (let index = 0; index < n_layers; index++) {
     lstm_cells.push(tf.layers.lstmCell(
      {units: rnn_output_neurons}));
}

model.add(tf.layers.rnn({
  cell: lstm_cells,
  inputShape: rnn_input_shape,
  returnSequences: false
}));

model.add(tf.layers.dense(
  {units: output_layer_neurons, inputShape: [output_layer_shape]
}));
```

Figure 8. Code of the RNN-LSTM model

```
Epoch #1 of #5 -- loss: 0.03320883960
Epoch #2 of #5 -- loss: 0.00506563298
Epoch #3 of #5 -- loss: 0.00179170608
Epoch #4 of #5 -- loss: 0.00021462121
Epoch #5 of #5 -- loss: 0.00007380049
slidingWindow: [ [ 0.0015, 0.0018, 0.0019 ] ]
ethereumPricePrediction: [ 0.0016082829097285867 ]
2023-05-13 : 0.001608283
```

Figure 9. Training the RNN-LSTM model

Transaction Price Predictions

Day	ETH Price	Price in Dollars
Friday 2023-05-12	0.0019	$3.42
Saturday 2023-05-13	0.0018	$3.24
Sunday 2023-05-14	0.0013	$2.34
Monday 2023-05-15	0.0015	$2.70
Tuesday 2023-05-16	0.0018	$3.24
Wednesday 2023-05-17	0.0013	$2.34
Thursday 2023-05-18	0.0014	$2.52

Figure 10.. Predicted Ethereum Transaction Prices for The Next 7 Days Using RNN – LSTM Model.

Since the model is of a time series forecasting, we use the Mean Absolute Percentage Error equation to calculate how accurate the results are. The values were predicted Ethereum transaction prices, versus the actual transaction prices recorded days later, over a period of 7 days. The dates were from the 13th May 2023 to the 19th May 2023.

$$\boldsymbol{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

$$\boldsymbol{M} = \frac{1}{7}\left(\left(\frac{-8.3937\times 10^{-5}}{0.0009}\right) + \left(\frac{-6.0153\times 10^{-5}}{0.0008}\right) + \left(\frac{-7.8666\times 10^{-5}}{0.0012}\right) + \left(\frac{-1.5088\times 10^{-4}}{0.001}\right) + \left(\frac{-1.20896\times 10^{-4}}{0.0009}\right) + \left(\frac{0.14486\times 10^{-4}}{0.001}\right) + \left(\right.\right.$$

$$+ \left(\frac{0.1455 \times 10^{-4}}{0.0009}\right))$$

$$M = \frac{1}{7}(0.0932 + 0.075 + 0.0655 + 0.15088 + 0.13429 + 0.14486 + 0.1455)$$

$$M = 0.1156$$

The equation yielded a MAPE value of 11.56%

The price prediction widget gives the user an overview on when to escape high transaction fees. It gives them the freedom to choose when to upload their reports, as once the report metadata is uploaded, it is immutable. Any new changes would require them to add a new block, resulting in more transaction fees.

When the patient is ready, they can then choose to add the report to the blockchain. When a user clicks the add report to blockchain button. The system checks if they have connected to a web3 wallet like MetaMask. A popup will then appear to connect them to their wallet. Once a successful connection has been established, he will be given options to set permissions on who will be able to view the report after it is added to the blockchain. If permissions are added for people using their email addresses, an email is sent to them with a link so that they can view that report. A viewer's page is there to load a record from the blockchain and authenticate said user so that they can view that particular report. On confirmation, MetaMask will display the price in Ethereum for adding a new transaction to the Ethereum Network.

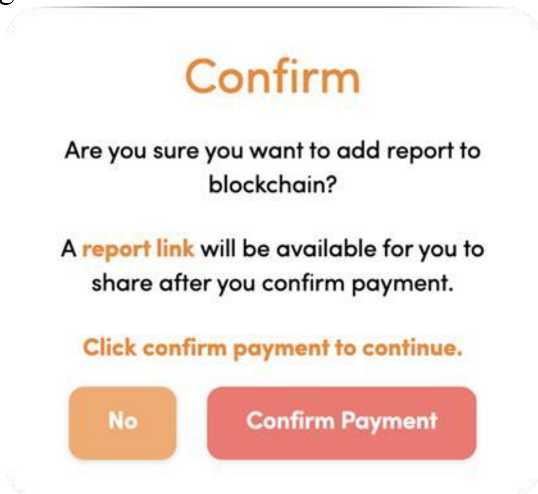

Figure 11. Confirmation Popup Before Adding Report To The Blockchain.

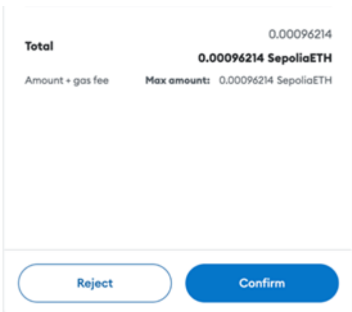

Figure 12. Confirmation Of Payment in MetaMask Wallet to Sign Contract Transaction.

When a new transaction is added to the Ethereum Network, it goes through an Alchemy Network Node that communicates our code with the contract on the chain. We wrote our contract in solidity, a JavaScript like language that runs on the Ethereum Virtual Machine. The contract consists of several functions to manage communication with our webapp. The most important ones are the addReport( ) and getReports( ) functions. They enable us to add new data onto the chain and to read data off it.

```
function addReport(
    string memory _reportID,
    string memory _reportName,
    string[] memory _reportPermissions,
    string memory _reportLink,
    string memory _reportOwnerName,
    string memory _doctorsEmail,
    string memory _ownersEmail,
    string memory _reportUploadDate
    ) public {

    Reports[_reportID]["reportName"] = _reportName;
    Reports[_reportID]["reportLink"] = _reportLink;
    Reports[_reportID]["reportOwnerName"] = _reportOwnerName;
    Reports[_reportID]["reportUploadDate"] = _reportUploadDate;
    Reports[_reportID]["doctorsEmail"] = _doctorsEmail;
    Reports[_reportID]["ownersEmail"] = _ownersEmail;

    ReportOwners[msg.sender].push(_reportID);
    GroupedIdentifiers[_doctorsEmail].push(_reportID);

    for(uint i = 0; i < _reportPermissions.length; i++){
        ReportPermissions[_reportID].push(_reportPermissions[i]);
    }

    emit LogReportProgress(_reportID,"report added");

}
```

Figure 13. Contract Function to Add Report Details to The Blockchain.

```
function getReport( string memory _reportID )
public view returns(string memory, string memory, string memory){
    return (
        Reports[_reportID]["reportName"],
        Reports[_reportID]["reportLink"],
        Reports[_reportID]["reportOwnerName"]
    );
}
```

Figure 14. Get Report Function to Fetch Report Details from The Blockchain.

When the user accepts to add a new transaction, the metadata from the database is written onto the contract using the addReport function and removed from the system. Adding report metadata to the Ethereum smart contract has a prerequisite which is to specify the link to the file, the owner's name, the permissions list of viewers, the Ethereum address of the owner, the doctor who created the report and the report ID. Once the transaction is complete, the patient will be able to see the new reports they have added to the Blockchain. This report is secure as only the owner and the people who have permission will be able to view its contents.

Figure 15. List of Reports on The Blockchain.

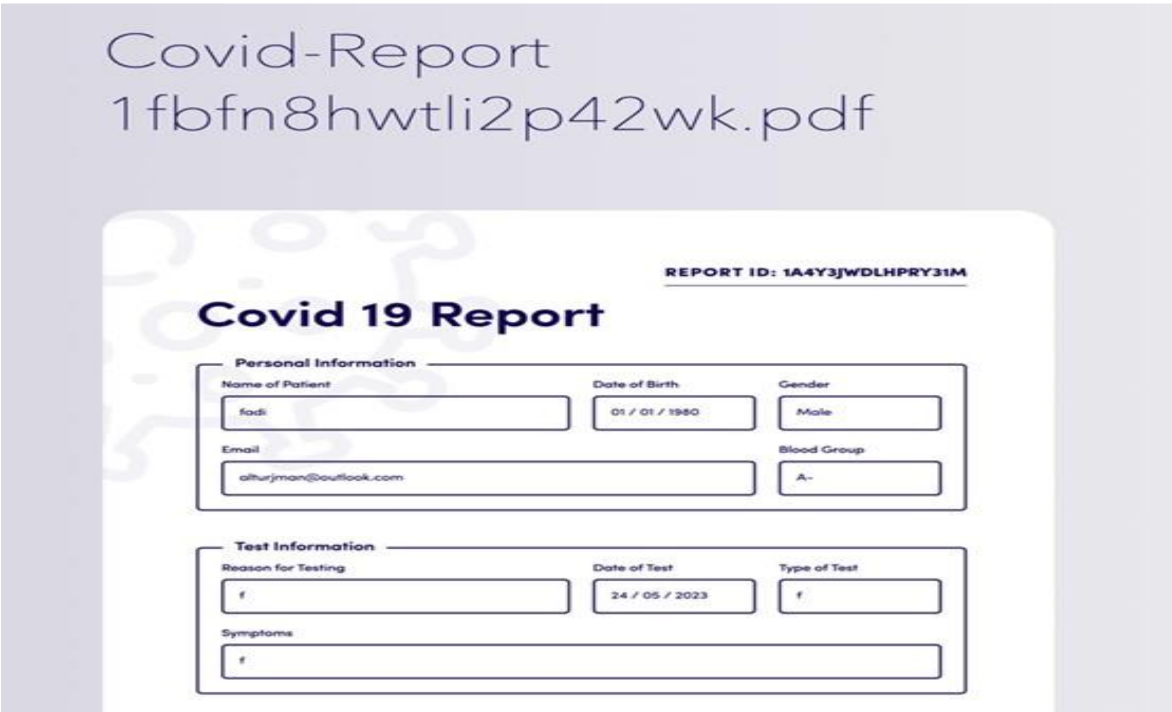

Figure 16. Report Link Guest View.

The patient will also be able to change permissions by adding new people and removing old ones who may not be allowed to view the report. However, this means that they will have to pay a price in Ethereum for any new transactions to the Blockchain. A link is also available if the patient would like to share it with a guest viewer. When someone is invited to view a report. The system connects to the Ethereum using Alchemy and checks if the viewer has the permissions to view the report. If so, the report will load, otherwise they will not be able to view anything.

Results and discussion

The results of the study demonstrate the effectiveness of implemented technologies in healthcare data management. The use of blockchain technology, specifically Ethereum, provided a decentralized and tamper-proof storage solution for medical records, ensuring data security, integrity, and privacy. This allowed patients to have more control over their healthcare decisions. The blockchain and cloud-based system enabled secure sharing of medical records among multiple healthcare providers, reducing the need for duplicative tests or procedures.

The integration of AI in healthcare data management proved beneficial in analyzing patient data and identifying trends and patterns that may be missed by human analysis. AI-based predictive models, such as the Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) models used in this study, provided insights into Ethereum blockchain transaction prices. This information can assist users in understanding potential impacts of the system and market trends, enhancing decision-making processes. The developed system's architecture, as shown in Figure 1, allowed for seamless communication between doctors, patients, and the cloud storage. The doctor's dashboard facilitated the creation and forwarding of medical reports, while the patient's dashboard provided access to the received reports. Smart filters ensured accurate routing of reports to the correct patients, improving efficiency and reducing errors in data handling.

The price prediction feature, based on the RNN-LSTM model, provided patients with realtime information on Ethereum transaction prices, empowering them to choose the optimal time to upload their reports and avoid high transaction fees. The model demonstrated a mean absolute percentage error (MAPE) of 11.56% when predicting Ethereum transaction prices over a 7-day period, indicating reasonably accurate predictions. The implementation of the system utilizing Ethereum blockchain and AI technologies showed promising results in healthcare data management. The secure and efficient storage and sharing of medical records enhanced decisionmaking processes, improved patient outcomes, streamlined operations, and potentially reduced costs. The combination of blockchain and AI technologies offers a synergistic relationship, enabling smarter and more secure applications in the healthcare industry.

There are still challenges which remain in terms of data interoperability, standardization, data privacy, and security. Further research and development are necessary to address these challenges and ensure the widespread adoption and effectiveness of blockchain and AI technologies in healthcare. This study contributes to the growing body of knowledge on the application of blockchain technology in healthcare data management. The healthcare industry holds significant potential for leveraging blockchain technology. When combined with advanced Machine Learning/Deep Learning algorithms and techniques, it has the power to bring about a revolutionary impact.

To build a more promising system, certain changes can be implemented:

1. Enhancing speed and efficiency: Introducing new consensus algorithms can greatly improve the speed and efficiency of adding and retrieving information within the blockchain system.
2. Overcoming data quality challenges: One major obstacle in utilizing Machine Learning in healthcare is the limited access to high-quality medical data. However, by adopting the proposed architecture for storing medical records, more up-to-date and accurate data can become available. This data can be securely utilized for training Machine Learning/Deep Learning models.

3. Improving model performance: By leveraging the newly available medical data, existing models can be further trained, enhancing their performance. This additional training leads to more precise predictions and better overall outcomes.

Conclusion

The proposed system provides a secure platform for the storage of healthcare data in the cloud and securing it using blockchain technology. As mentioned earlier, blockchain provides accessibility, security and trust the networks for the patients' data. The findings highlight the potential benefits of integrating cloud, blockchain and AI technologies in creating secure and efficient systems for managing and sharing medical records, ultimately leading to improved healthcare outcomes and patient care.

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ARTIFICIAL INTELLIGENCE FOR REMOTE PATIENT MONITORING IN IOT-BASED HEALTHCARE APPLICATIONS – AN OVERVIEW

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Abstract: Through m-Health and e-Health, a number of services are provided remotely, including avoiding illnesses and treatment, evaluation of risk, medical monitoring, learning materials, and treatment. The popularity of mobile health and electronic health care in society is due to this. For mobile health and electronic health, the development of modern Internet of Things (IoT) devices and systems can be particularly beneficial. There are several IoT electronic health care and mobile health designs that have been developed that can manage an emergency situation well. However, traditional electronic health and mobile health systems don't use smartphone sensors to gather and communicate crucial patient health data. In this study, we investigated m-Health and eHealth, which use body sensors and smartphone sensors to gather, analyse, and transmit client information regarding health for standardized cloud storage. Patients and other participants may later be able to access the data that has been kept. The findings of the current research revealed the trending classical machine learning models in AI-based RPM, yet, with a note-worthy absence of the latest generation deep learning techniques such as Transformers. The noted advantages of applying AI-based RPM include amongst others; enhancing medical care, accelerating treatment, and lowering expenses. We have made suggestions for offer the AI, IoT and mobile technologies that could be applied to achieve improved RPM solutions.

Keywords: AI, IoT, Healthcare, Mobile Technology

1. Introduction

Digital technology advancements, particularly in mobile smartphone technology, have sparked a wide range of creative approaches aimed at enhancing patients with chronic conditions' capacity for self-management. In fact, overall self-management programs have proven effective in enhancing outcomes for significant chronic conditions, including diabetes and hypertension. Using a conceptual model to measure vital parameters like electrocardiogram (ECG), temperature, etc. with an artificial intelligence-based health monitor, this research will concentrate on the uses of sensors for designing patients' self-management tools. These tools will help patients manage their own health problems, or those of their family members, from outside the walls of institutional structures.

2. Literature review

The study evaluated the use of IoT-based medical applications, and it suggests an IoT-Tiered Infrastructure (IoTTA) as a means of turning information from sensors into useful clinical data. This approach considers a variety of elements, such as quarrying, detecting, transferring, analysing, storing, and interpreting [1]. Proposed using smart contracts that are built on top of block chains to make it easier to track and evaluate embedded devices securely using a private block chain based on the Ethereum protocol, an infrastructure wherein the instruments communicate with an intelligent device that executes intelligent agreements and tracks all events on the block chain was constructed. Real-time tracking of individuals and medical care would be possible by sending notifications to patients and medical professionals and preserving a secure record of who initiated these measures [2]. The World Wide Web, the Internet of Things, also known as IoT, and smartphone and tablet advancements have made remote patient monitoring considerably more practical. Wearable technology is already being embraced by healthcare professionals to expedite diagnosis and treatment. Patients benefit from an inherent ease of service. As needed, patients can maintain contact with medical professionals. Also, it lowers medical expenses and raises the standard of care [3]. Remote health monitoring systems (RHMS) use telecommunications technology to provide quick medical treatments in remote areas. RHMS is becoming a useful aspect of modern medicine as a result of considerable technological advancements, particularly in wireless internet, the use of cloud computing, and information storage. RHMS contributes significantly to the sustainable delivery of exceptional healthcare services to individuals with multiple chronic diseases (MCDs). [4]. Telecommunications technology is used by systems for remote health monitoring (RHMS) to deliver prompt medical care in remote locations. Due to significant technical improvements, notably in wireless internet, cloud computing, and data storage, RHMS is becoming a vital component of contemporary medicine.

RHMS makes a substantial contribution to the sustainable provision of outstanding healthcare services to people with multiple chronic illnesses (MCDs) [5]. An algorithm was suggested to forecast patients' present health state in conjunction with ongoing monitoring in contact with their medical providers [6]. IoT is being used as an accelerator to increase the efficacy of AI uses in the medical industry. IoT sensors are used to collect health information, which is then evaluated using methods based on machine learning. The created healthcare paradigm will practitioner in making an early illness detection [7]. The block chain-assisted safe information management system has been suggested to increase flexibility and data availability in the field of healthcare and safeguard the exchange of patient data. Secure information interchange between private servers and cloud servers, as well as between private servers and embedded medical devices, is made possible. Block chain technology is used by the IoMT-based security architecture to provide data management and transmission security between devices connected [8]. To look into the literature, five databases were chosen (science Simple, IEEE-Explore, Springer, PubMed, and science.gov). It applied the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology, which is the accepted method for systematic reviews and meta-analyses. Presented the tracking system for chronic illnesses as a case study to provide better remote patient monitoring. [9]. Initially investigated the difficulties with data acquisition for privacy protection.

Later, with the aim of preventing these kinds of assaults, present a useful framework called Security Protector, patient privacy protected data collecting. Privacy Protector integrates the ideas of confidential sharing with share-mending (in the case of data loss or breach) for the security of patient data) [10]. The research makes it possible to find and continuously monitor the health of soldiers who get separated or harmed on the field of battle. As a result, army control unit search and rescue operations require less time and effort. The technology enables the army control unit to follow soldier movements and check their health by utilizing satellite and body-part networked sensors like thermometers and heart rate monitors. For further data analysis and clustering using the K-Means method computations, the collected data will be transferred to the cloud [11]. IoT technology may be utilized to boost the efficacy and user satisfaction of health care services, including monitoring patients remotely, real-time medical issue diagnosis, and beyond. The proposed research aims to forecast heart illness using machine learning (ML) methods for categorization. IoMT-based cloud-fog diagnostics for heart disease have been proposed. ML classification techniques are used with the fog layer to quickly analyse health data [12]. The article reviews the latest developments in the field of peripheral and cloud computing, how it works with the Internet of Things, and the benefits and challenges of applying the fog framework to applications related to healthcare. It also covers various edge and fog computing architectures and how they may be used to improve new IoT applications, as well as potential future research paths in cloud computation and AI within the perimeter layer of Internet-based applications [13].

More than ever, healthcare delivery may be sped up by merging cloud services with cutting-edge technologies such as big data statistical analysis, AI, and the Internet of Medical Interventions. It increases capacity, raises compatibility, and brings down prices [14]. This work has demonstrated the modelling and building of a synthetic intelligence-based health care tracking (PM) platform to measure important parameters for the prediction of diabetes mellitus. The study conducted a brief analysis of diabetes and an artificial intelligence (AI) model based on a fully connected neural network's machine learning (ML) algorithm (FNN). The way the suggested system operates allows for a very straightforward yet appropriate solution to the diagnosis of diabetes mellitus while still reducing computing complexity. [15]. It is important to look at low-power, high-efficiency alternatives to compression that enable the gathering, delivery, and evaluation of electrocardiogram (ECG) data on a linked home or other distant server. The proposed method addresses the growing need for enhanced remote health monitoring by providing an advantage for the speedier and more efficient immediate delivery of ECG values [16]. It is important to look at low-power, highefficiency alternatives to compression that enable the gathering, transfer, and subsequent examination of electrocardiogram (ECG) data on a linked home or other distant server.

The suggested technique offers an advantage for the quicker and more effective real-time transmission of ECG readings, which satisfies the rising need for improved remote health monitoring. This research proposed a fitness band with a biological recognition facial mask to measure a patient's pain level using a face electromyogram (sEMG). The study demonstrated scalable IoT systems for real-time biological dynamic tracking and wearable sensors for automatic pain rating using facial expressions. [17]**.** Chronic illness situations, psychiatric, emotional health, economics, and encompassing situations are the five key subcategories of parameters that are examined. In order to find any potential connections between variables in various categories, they are examined in the context of states and regions within the United States [18]. The aim is to develop a stochastic framework to predict important patient management issues based on current and historical values of a number of physiological indicators. People with chronic diseases living alone at home often die from various diseases because there is no effective computational approach to predict abnormalities in physiological parameters. The temporal behaviour of six biological signals is used to drive the Hidden Markov Model (HMM) used to predict various clinical events [19]. Using a cloud-based approach, the technology enables the anaesthesiologist to disseminate and monitor the mobile application concurrently.You can keep an eye on many patients at once.

This technology's main advantage over more traditional approaches is that it is secure and requires fewer resource. The Android software assists many patients simultaneously, making it straightforward for the surgeon to monitor various treatments at once [20]. A unique method of ECG monitoring was created using the Internet of Things, or IoT, concepts. ECG data is gathered by a wearable monitoring node and transferred directly via Wi-Fi to the IoT cloud. Both the Hypertext Transfer Protocol (HTTP) and MQTT protocols are used in the Internet of Things cloud to provide customers with quick and obvious ECG data. [21]. Demonstrated a ubiquitous monitoring system that may instantly transmit a patient's vital signs to distant medical applications. Researchers assess the danger to patients, the requirements for medical analysis, the needs of communication, and the demands on computing resources before presenting four data transmission strategies. Eventually, a sample prototype is put into use to give a conceptual model [22]. The home gateway's issues with data overload and network congestion are handled using an ECG compression approach. According to a system demonstration, the ECG signals and movement signals of the elderly may be monitored. Reviewing the compression technique indicates that it has an excellent proportion of compression, little distortion, and is quick, making it ideal for residential gateways. The suggested solution is easy to use and has strong scalability. It provides an opportunity to offer elderly people ongoing, long-term home health monitoring services [23]. Doctors will be able to help patients make the best decisions by continuously monitoring patients with chronic conditions. Patients can also lead regular lives as usual.

The patient does not need to stay in the hospital, which also saves money. We believe that the novel design that has been proposed is feasible and that it will significantly improve the patient's standard of living while also substantially reducing spending on healthcare. [24]. Globally, diabetes is becoming more common. Diabetes patients require ongoing surveillance, and in order to accomplish this goal, they must participate in the process of managing their healthcare. A technology-driven movement called mobile health (MH) aims to provide chronically sick individuals more control over their lives in modern settings. To address the limits of MH innovations, it is necessary to talk about their present condition. A comprehensive examination of the research from this angle is beneficial for both intellectual and practical advancement. The limitations that have not yet been entirely overcome are critically analysed in this work, and future research paths that can increase the application of MH are also highlighted [25]. Described in depth a number of current RPMS with an emphasis on their use, architecture, technologies used, and difficulties they encountered. At last, a summary of quality of performance (QoP), one of RPMS's challenges, is provided. Also carried out a statistical assessment of the available literature.

The studied requirements for quality of service based on traffic type, data quality, device quality, and network metrics are offered with the intention of giving the most recent knowledge for academics and enterprises to adapt to when creating quality-aware RMPS [26]. The study includes the relationship between big data attributes and remotely comprehensive health care monitoring is discussed in the context of patient ranking. The spotlight is focused on the unresolved problems and difficulties with large data employed in patient prioritization. As a suggested remedy, selecting the huge data of chronically ill patients based on the most critical instances involves making decisions using several criteria, such as vital signs and primary issues [27]. A computer Innovation system for remotely monitoring the health of CVD patients is proposed. The system includes a variety of health sensors for detecting the heart rate, temperature of the body, cardiac output, and composition of the body. A virtual assistant also does a general medical examination.

All of the patient's current health-related data is acquired by the Microprocessor (processing unit) using these sensors and a Chabot, and using the highest-accuracy Machine Learning (ML) algorithm, it automatically diagnoses the data and recommends medications to the patient. The final health report is then transferred to the doctor's device for evaluation [28]. Reviewed the already known research and discusses the best ways to employ Internet in the realm of medical and intelligent healthcare. Second, a fresh semantic framework for client electronic health care was proposed. The sensing layer, the layer of networks, the web layer, as well as services layer are the four components that make up the 'k-healthcare' paradigm. All Levels must effectively interact in order to develop a platform that will allow people with mobile devices to access medical information about patients. [29]. Mobile technology' apparent difficulties have prevented their wide usage in clinical studies. Studies utilizing mobile technology continue to be supported by the same scientific standards that underlie the clinical trials industry. These suggestions offer a structure for incorporating mobile technology into clinical trials, which may facilitate a more thorough evaluation of potential novel treatments for patients [30]. With regard to performance, acceptability, accessibility, practicality, cost, and efficacy in dengue, Zika, and chikungunya monitoring, the goal of this scoping review is to examine the evidence of the use of mobile phones as intervention tools [31].

The suggested hardware comprises of a single-chip microcontroller (RFduino) that has Bluetooth low energy integrated, which reduces space and increases battery life. In a lab setting, the "smart case" system has undergone testing. Also created a 3-D-printed smartphone cover to verify the system's viability. The outcomes showed that the suggested system may be on par with high-caliber medical equipment [32]. In the area of healthcare for persons with chronic diseases, such as diabetes, wearable technology has gained a lot of scientific interest. They have the power to lessen the effects of diabetes and its consequences, as well as help control the disease. Moreover, these gadgets have enhanced the quality of life and disease management. [33] The results showed that a perceptron with several layers may detect diabetes effectively from the individual's data collected from sensors after machine learning-based classification algorithms were tested on a diabetes dataset. Additionally, the results demonstrate that, utilizing the information from the present sensor, extended selective memory may accurately predict the blood glucose level in the future. To further enhance patient health and prevent serious diseases in the future, the suggested diabetes categorization and BG prediction might be integrated with recommendations for a patient's overall diet and level of physical activity [34]. In order to better understand how customers, particularly the elderly and caregivers, perceive wearable gadget technologies, research was conducted.

The investigation was carried out using a survey method that was delivered to older people and their caregivers. The anticipated outcomes of this study may be used in the development of product and service offerings by technology entrepreneurs so that they meet consumer expectations and improve consumer well-being in an older population [35]. In the upcoming years, it is projected that the forthcoming generations of continuous glucose monitors will incorporate advanced algorithms due to the recently proven effectiveness of a number of recently proposed methods for improving sensor performance. Due to the increased accessibility and dependability of current and contemporary CGM devices, a sizable amount of data will be produced in the upcoming years that will eventually be accessible for offline analysis. Since CGM usage is cyclical, it is reasonable to assume that some recently suggested methods, like retroactive testing and maximizing diagnostic dimensions based on historical data, will be very beneficial for continuous glucose monitor outcomes throughout their lifetime, enabling their evaluation and enhancement over time. [36].

The approach lessens the need for calibrations while maintaining (and occasionally improving) CGM sensor precision compared to that of the equipment designer. Reduced calibration requirements make CGM technology easier to use and less expensive to deploy, which is a necessary condition for using it to replace conventional blood glucose measurement sensors [37]**.** Compared to the static, non-updating calibration technique, the updating approach demonstrated a relative improvement in CGM accuracy, although it was not statistically significant. It is anticipated that the sensor's performance would gradually increase with the utilization of data gathered over a longer duration [38]Hopkins, a state-of-the-art mobile phone monitoring platform, was developed to assess symptoms both actively (data are obtained when a set of tests are begun by the user at specific times during the day) and quietly (data are continually gathered in the background).

During data collection, take note of traits that may be used to assess the voice, balance, gait, flexibility, and response time that are associated with PD symptoms. Measurements recorded after a dosage of medicine (treatment) vs. before the dose are distinguished using a random forest classifier (baseline) [39]A small handheld instrument was developed that can monitor the temperature of the body and the amount of blood sugar in diabetics in order to validate the proper operation of this system. This technology is used to determine whether a variable has exceeded a threshold and may or may not be included in the proposed architecture. To establish a wireless connection with the mobile device, a secure technique was designed [40]. Presented a thorough MH framework with integrated CDSS capabilities. Its cloud-based technology keeps tabs on and controls type 1 diabetes.

The quality of any CDSS's knowledge and the extent to which it can interact meaningfully with multiple data sources determine how effective it is. The goal of this project is to do this by developing a conceptual clinical decision support system based on the suggested FASTO taxonomy. A variety of patient data may be gathered, formalized, integrated, processed, and otherwise manipulated using the practical ontology. It provides clients with thorough, customized, and scientifically understandable care plans that include everything from insulin regimens to diets to exercise habits to training sub-plans. These plans are based on the whole patient's information. The recommended CDSS furthermore offers wireless body area networks for patients that collect vital signs for real-time monitoring at home [41]. Metabolic biomarker profiling that is quick, precise, portable, and quantifiable is crucial for the diagnosis and prognosis of diseases. For the purpose of metabolism monitoring, current advancements in optical and electric biosensors based on smartphones are promising due to their benefits of speed, dependability, accuracy, affordability, and multianalyse analysis capacity. Electrochemical bio sensing systems, including wired and wireless communication, as well as optical bio sensing platforms, including colorimetric, fluorescent, and chemiluminescent sensing have been discussed. The difficulties and expected future scenarios for multifunctional, dependable, accurate, and affordable mobile phone bio sensing devices were also explored [42].

3. IoT in Medical Applications

The characteristics of IoT devices, and applications that have been used in m-Health and ehealth have been analysed in this section.

Table 1: Summary table of data extracted from reviewed papers, showing the sensor types, measured parameters, disease and device types

Ref	Type of sensor	Parameters	Type of disease	Iot monitoring type	Devices an apps used
[1]	(IoTTA)	ECG, Oxygen Saturation (SpO2), pulse rate, heart rate, and weight	Chronic diseases	IoTTA architecture	IoT healthca applications
[2]	medical sensors	HealthContractCaller, heartrate Monitor (),	high blood pressure, diabetes	Wireless Body Area Networks (WBANs)	Oracle
[3]	Accelerometer, Pulse Oximeter, Heart Rate Monitor Device	N/A	Chronic disease and mental health disorders.	blockDAG (block chain system)	GHOSTDAG block chain based smar contracts, wearable devices, Orac smar devices o smartphones.
[4]	N/A	N/A	chronic diseases heart rate and blood pressure, fever, high BP and diabetes	patient monitoring using mobile adhoc network	N/A
[5]	Wearable sensors	QoS (Quality of Service) parameters,	heart diseases,	ECG monitoring system	N/A

		Air Quality Indicators (AQIs)		chronic disease		
[6]	YL69 moisture sensors and DHT11 (Temperature & Humidity sensor), body sensor network (BSN)	(AI-IoT)		heart diseases,	Patients data storage (PDS) Health Data Allocating Policy (HDAP) Cloud Middleware (CM)	raspberry Arduino
[7]	IoT Body implanted sensors	N/A		Temperature, heartrate, heart disease, diabetes breast cancer, hepatitis, liver disorder, dermatology, surgery data, thyroid blood pressure.	DT, SVM, NB, AB, RF, ANN and K-NN	Automatic Multi-Layer Perceptron (Auto MLP application the prediction o diabetes.
[8]	IoMT devices such as smart watch and mobile devices.	BSDMF,	PPEOTF)		IoMT-SAF, (MDPAC)	(BIoMT)
[9]	pulse oximeter, gyroscopes, a spirometer, a global positioning system (GPS), and electrooculography (ECO)			cancer, diabetes	Cloud health monitoring system	pulse oximete gyroscopes, spirometer, (GPS), (ECO)
[10]	IoT sensor	Privacy Protector, SW-SSS		N/A	(PDAC)	
[11]	(WBASNs), GPS, Heartbeat sensor, ECG module	GSM		heartbeat, body temperature	LoRaWAN	IED,LoRaWAN ZigBee
[12]	Temperature sensor, heart rate	N/A		heart disease		(FAHP)

	sensor, ECG, SPO2					
[20]	(WBSN)	ZigBee, SMS	GSM and	heart rate, blood pressure, temperature	ECG, EMG monitoring	Android app
[9]	infrared sensor	GSM		heart rate, blood pressure for	automatic saline monitoring system	Android app

			coma patients		
[21]	ECG sensor	Wi-Fi module, server,	heart diseases, the arrhythmia Drug toxicity.	ECG monitoring	N/A
[24]	(WBAN)	electro cardiogram (ECG), electroencephalogram (EEG), body movement, temperature, blood pressure, blood glucose, heartbeat, and respiration rate levels)	(Blood pressure, fatigue level (EEG), heart rate, respiratory rate, SPO2 saturation)	galvanic skin response (GSR), Electrocardiogram (ECG)),	N/A
[27]	medical sensors GPS	(MCDM)	heart, diabetes, and BP)	N/A	N/A
[15]	wearable blood pressure sensor, temperature sensor, and ECG sensor	N/A	diabetes,	blood pressure Electrocardiogram (ECG) temperature	Patient Monitoring (PM) prototyp device
[40]	glucose motion temperature	Bluetooth	diabetes,	continuous glucose monitoring (CGM)	smartphone
[29]	smartphone sensors	3G or Wi-Fi	Blood pressure, ECG	N/A	Samsung Note / S4
	temperature sensor (DSB18B20), blood pressure sensor (sphygmomanometer), heart rate sensor (pulse sensor) and ECG sensor (AD8232)		measuring heart rate, Blood Pressure (BP), ECG, Body Mass Index (BMI), body temperature		MedX' bot

Table 2: Summary of performance analysis of IoT sensor-based disease diagnosis with AI models

#	Model / algorithm Used	Health Application	Reported accuracy
[1]	IoTTA architecture	Self-care.	96.4%
[7]	DT, SVM, NB, AB, RF, ANN and K-NN	Heart disease, diabetics, breast cancer, hepatitis, liver disorder, dermatology, surgery data, thyroid.	93.32%
[12]	IoMT-based	Mechanism for tracking medical conditions to detect cardiac disease.	(97.32%).
[8]	block chain and IoMT	Dynamical assembly of patients' sensor data and running on smartphones and wearables, with focus on Privacy and security of healthcare data.	97.2%,
[19]	(HMM)	Hidden Markov model is used to learn and categorize different clinical occurrences based on the behaviours of many different vital signs. Using the knowledge gained from the changes in several physiological markers, this approach is also appropriate for continuous patient's monitoring.	97.8%

[11]	K-Means Clustering algorithm	Using a LoRaWAN transceiver to send data from the squad leader to the control unit and a ZigBee transceiver to provide data from a faraway soldier to the squad leader and other troops. The K-Means algorithm for machine learning and a range of sensors are used by the system to help in forecasting the warzone scenario, tracking soldier health data, and identifying nearby weapons..	N/A
[40]	naïve Bayes, J48, ZeroR, random tree, SMO, and OneR	In addition to monitoring patient health data like glucose levels to help with analysis and diabetes diagnosis, the system also offers cutting-edge capabilities like compatibility, local storage, and information processing.	99.17%,
[29]	k-Healtcare model	Uses four phases that closely cooperate to offer effective data storage, processing, and retrieval.	N/A
[23]	ECG compression algorithm	It can provide elderly people continuous, longterm monitoring. The compression algorithm's test results demonstrate the viability of using the method to compress with a real-time monitoring system.	N/A

This work has presented a thorough analysis of the advantages of smartphones as RPM sensors in this study. Modern smartphone-based mobile bio sensing devices have the ability to bring medical testing into non-clinical settings for the best and most individualized treatments of metabolic illnesses. These devices will enable daily and thorough metabolic monitoring. The period for these studies was from 2016 to 2023. The researches reveal various advantages, including the capability of ongoing remote patient monitoring and the availability of real-time online patient health data based on algorithms, provides precise detection. High accuracy in diagnosis capabilities, outstanding performance in home medication management, and early clinical aggravation detection are all provided. Offers individualized diagnoses and very precise prediction algorithms. The classification accuracy is described as an assessment metric to contrast the outcomes of various methods used in the dataset. A table provides measurement accuracy in research studies varies from 96 to 99 percent. An exciting prospective issue is the use of sensing for monitoring patients from afar using cell phones. This idea has significant promise for acquiring trustworthy, accurate, and affordable diagnoses from a large number of analysts in resource-constrained and non-clinical circumstances. For this research on the use of devices for remote patient monitoring, I assessed important data from specialized wearable devices as well as data from specialized embedded or passive sensors. Additionally, recent advancements in mobile and portable testing for individual health care at home have highlighted difficulties in acquiring a variety of analytical diagnoses in non-clinical settings that are trustworthy, accurate, and reasonably priced. Some studies, such as Monitoring without Follow-Up, have some flaws. Some systems are manual; for instance, patients take measurements and report results. Most systems are not flexible enough to allow for the addition of new sensors while they are running. Not enough clinically proven guidance and instructions are offered. There is still little patient engagement in the delivery of care. Algorithms for clinical assistance are not used enough. - Effective data mining for high level outcomes is lacking.

4. Conclusion

In this work, we performed a thorough evaluation of RPMs. We focussed our study on RPMs from a software viewpoint (i.e., kind of sensors, monitoring type, parameters employed, algorithm, and level of accuracy). Our research showed that multiple models using machine learning have been developed specifically for RPM, showing good accuracy levels between 97% and 99%.Despite the extensive application of Machine learning models, we noted the absence of the latest technologies of deep learning such as Attention mechanisms and Transformer models applied for training models in the domain of RPM. This constitutes an open ground for research, considering the ground-breaking accuracies achieved by these models in other domains.

This study may help researchers plan future research to address issues and limits, as well as assisting future researchers interested in RPMs in understanding the degree of evidence that is now accessible in the literature. RPMs include the complete lifespan of monitoring systems, including the briefly covered backend systems, cloud systems, and wireless sensors and devices. Like every research method, the one employed in this study has limits as well as a number of potential applications in medical care field.

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APPOINTMENT SYSTEM USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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Abstract- This project aimed to design and implement an AI-enabled hospital appointment booking system using a combination of PHP, MySQL, HTML5, CSS, Python, and JavaScript. The system aimed to address the challenges of traditional appointment booking systems by providing an intuitive and efficient platform for patients, doctors, and hospital staff. The user interface was designed using HTML and CSS, with interactivity added through JavaScript to enable a multi-step booking modal. The backend requirements were fulfilled using a combination of jQuery Ajax and PHP, with appointment data stored and retrieved from a MySQL database. The logic to avoid booking clashes was implemented using PHP. Additionally, a machine learning model was trained using Python and data from the AI&IoT health app to predict the optimum period of the day to book an appointment based on the day of the week and desired service type. The integration of AI components aimed to optimize scheduling, reduce congestion, and provide a seamless experience for users. The project's implementation showcased the successful integration of various technologies to create an intelligent appointment booking system for enhanced healthcare services.

Keywords: Appointment booking, health application, Artificial Intelligence, Healthcare, Time scheduling.

1 Introduction

The healthcare industry plays a vital role in society, ensuring the well-being and timely medical attention of individuals. However, the process of scheduling appointments in hospitals has long been plagued by inefficiencies, long waiting times, and miscommunication. To address these challenges, this project introduces an AI-enabled hospital appointment booking system that harnesses the power of advanced technologies to revolutionize the way appointments are managed.

In this era of rapid technological advancements, the integration of artificial intelligence (AI) has the potential to significantly enhance the efficiency and effectiveness of healthcare services. By combining PHP, MySQL, HTML5, CSS, Python, and JavaScript, this project aims to design and implement a comprehensive solution that streamlines the appointment booking process, improves patient experiences, and optimizes resource allocation for hospitals.

The user interface of the system is meticulously crafted using HTML and CSS, ensuring an intuitive and visually appealing experience. Interactivity is introduced through JavaScript, allowing for a multi-step booking modal that guides users through the appointment scheduling process. This intuitive interface empowers patients, doctors, and hospital staff with a userfriendly platform that simplifies appointment management.

To fulfill the backend requirements, a combination of PHP and jQuery Ajax is utilized. PHP serves as the backbone for processing and storing appointment data in a robust MySQL database, ensuring secure and reliable access to information. By leveraging these technologies, the system can handle a significant volume of appointment requests and concurrent users, optimizing performance and responsiveness.

One of the key challenges addressed by this project is the prevention of booking clashes. Through intelligent algorithms implemented in PHP, the system analyzes and detects conflicts, thereby eliminating scheduling errors and reducing inconvenience for patients and doctors. By avoiding congestion and optimizing appointment slots, the system ensures efficient utilization of hospital resources, resulting in enhanced operational efficiency. Furthermore, this project incorporates an AI component powered by Python and data collected from the AI&IoT health app. Through machine learning algorithms, the system predicts the optimal period of the day to book appointments based on the day of the week and the desired service type. By analyzing patterns and trends, the AI component helps users make informed decisions, avoiding unnecessary waiting times and improving overall satisfaction.

The integration of AI technologies brings numerous benefits to both patients and healthcare providers. Patients experience a more fluid and personalized appointment booking process, reducing stress and enabling them to access timely medical care. Hospital staff and administrators benefit from optimized resource allocation, improved workflow management, and enhanced patient satisfaction. This project presents an innovative approach to revolutionizing healthcare by introducing an AIenabled hospital appointment booking system. By combining PHP, MySQL, HTML5, CSS, Python, and JavaScript, the system offers an intuitive user interface, efficient scheduling, and intelligent optimization. Through the integration of AI technologies, it empowers both patients and healthcare providers, creating a seamless experience and enhancing the overall efficiency of healthcare services. This project paves the way for a future where technology-driven solutions transform healthcare delivery and improve patient outcomes.

2. Problem Statement

The current process of scheduling appointments in hospitals is plagued with inefficiencies, long waiting times, and miscommunication. Patients often encounter difficulties in securing timely appointments, while doctors and hospital staff struggle to manage their schedules effectively. Moreover, the lack of intelligent optimization leads to scheduling conflicts and resource underutilization, resulting in decreased operational efficiency. To address these challenges, there is a critical need for an AI-enabled hospital appointment booking system that streamlines the appointment management process, enhances patient experiences, and optimizes resource allocation. The system should provide a user-friendly interface for patients to schedule appointments seamlessly, enable doctors to manage their schedules efficiently, and facilitate real-time updates for hospital staff. Additionally, the system should integrate AI components, such as natural language processing and machine learning algorithms, to intelligently schedule appointments, predict optimal booking periods, and improve overall efficiency. By tackling these issues, the proposed solution aims to revolutionize healthcare services and provide a streamlined and intelligent platform for hospital appointment management.

3. Review of Related works

The adoption of artificial intelligence (AI) in healthcare has the potential to revolutionize appointment booking systems, enhancing efficiency, optimizing resource allocation, and improving patient experiences. This review explores a collection of papers that contribute to the theme of AI-enabled appointment booking systems in healthcare. These papers showcase innovative approaches, ranging from web applications to mobile applications and machine learning algorithms, aimed at streamlining the appointment management process. By critically analyzing and synthesizing the findings of these papers, we gain insights into the advancements and challenges associated with AI-enabled appointment booking systems.

[1] M. A. Noori, S. A. S. Hussien, and T. A. Al-Janabi present a paper on "Blood donors appointment booking and managing system using PC and mobile web browsers in current pandemic (COVID-19)" [1]. The authors propose a system that leverages web browsers to facilitate blood donor appointment booking. The study addresses the challenges posed by the COVID-19 pandemic and provides a solution to manage blood donations efficiently.

[2] S. V Patil, S. B. Patil, O. A. Terdalkar, and B. S. Yelure contribute a paper titled "Smart Web Application for Efficient Management of Hospital Appointments" [2]. Their research focuses on developing a smart web application that optimizes hospital appointment management. The authors emphasize the importance of an efficient scheduling system to minimize waiting times and improve patient satisfaction.

[3] F. Mohd and N. I. Elanie Mustafah present the paper "'Hello, Dr': A Healthcare Mobile Application" [3]. The authors propose a healthcare mobile application that facilitates appointment booking and communication between patients and doctors. The study highlights the potential of mobile applications in enhancing healthcare services and improving patient-doctor interactions.

[4] I. B. Aishwarya, D. Unni, V. S. Rakesh, and S. Swapna Kumar contribute to the field with their paper titled "Smart token booking system for hospitals" [4]. Their research focuses on developing a smart token booking system that streamlines the appointment process in hospitals. The authors emphasize the importance of a user-friendly interface and efficient token management to improve the overall patient experience.

[5] P. R. Cronin and A. B. Kimball present a paper titled "Success of automated algorithmic scheduling in an outpatient setting" [5]. The authors investigate the success of automated algorithmic scheduling in an outpatient healthcare setting. Their study demonstrates the effectiveness of automated scheduling algorithms in reducing patient waiting times and improving resource utilization.

[6] A. Yelne and A. Raut contribute to the field with their paper "Digital Health-Care System for Smart IPD Booking" [6]. The authors propose a digital health-care system that enables smart inpatient department (IPD) booking. Their study emphasizes the importance of digitization in improving the IPD booking process and enhancing hospital operations.

[7] F. Piccialli, S. Cuomo, D. Crisci, E. Prezioso, and G. Mei present a paper titled "A deep learning approach for facility patient attendance prediction based on medical booking data" The authors explore a deep learning approach to predict patient attendance at healthcare facilities based on booking data. Their study highlights the potential of machine learning algorithms in forecasting patient attendance, allowing for better resource planning and allocation.

The paper by Odeh et al. [8] presents a smart software system for medical patient appointments management in the UAE. The study highlights the use of AI algorithms to optimize appointment scheduling, reducing waiting times and enhancing patient experiences. The authors demonstrate the effectiveness of their system in improving appointment management processes, leading to enhanced operational efficiency in healthcare settings.

Zea and Gutierrez [9] discuss the development of a mobile platform for managing hospital appointments using Bluetooth Low Energy (BLE) technology with external devices known as Beacons. The paper showcases the utilization of AI techniques to improve appointment scheduling accuracy and enable real-time updates. The integration of BLE technology enhances the system's efficiency by enabling seamless communication between patients and healthcare providers.

In the work by Sujatha et al. [10], the authors explore the concept of smart healthcare development and emphasize the role of AI in transforming healthcare systems. The paper highlights the potential of AI-enabled appointment booking systems to optimize resource allocation, improve patient access to healthcare services, and facilitate sustainable smart city development. The authors provide insights into the benefits and challenges of implementing such systems, laying the foundation for future advancements.

Lupton [12] offers critical perspectives on digital health technologies, including AI-enabled systems. The paper examines the ethical implications, privacy concerns, and potential social impacts associated with the adoption of these technologies in healthcare. It raises important questions regarding the fairness, transparency, and accountability of AI algorithms used in appointment booking systems, emphasizing the need for responsible implementation and regulatory frameworks.

Evangelista et al. [13] investigate the satisfaction and appointment access of patients in paediatric nurse practitioner-managed cardiology clinics. While not directly focused on AIenabled systems, the study sheds light on the importance of efficient appointment scheduling in improving patient experiences. The findings highlight the significance of streamlined appointment booking processes in enhancing patient satisfaction and accessibility to specialized care.

Kevat et al. [14] present an online referral and immediate appointment selection system that empowers families and improves access to public community paediatric clinics. Although not explicitly AI-enabled, the study demonstrates the potential benefits of leveraging technology to enhance appointment management. The system streamlines the referral process, reduces waiting times, and provides patients with greater control over their healthcare journey.

3.1 Synthesis of reviewed literature

The reviewed papers collectively highlight the potential of AI-enabled appointment booking systems to revolutionize healthcare services. These systems utilize AI algorithms to optimize scheduling, enhance patient experiences, and improve resource allocation. However, ethical considerations, privacy concerns, and regulatory frameworks must be carefully addressed to ensure responsible and fair implementation. The studies also emphasize the importance of streamlined appointment booking processes in improving patient satisfaction and accessibility to healthcare services. Overall, the advancements in AI technology offer promising opportunities for the transformation of appointment management in healthcare, leading to enhanced efficiency and improved patient outcomes.

4 Methodology and Implementation

4.1 Requirement Analysis:

To identify the specific requirements and functionalities of the AI-enabled hospital appointment booking system, we conducted a thorough analysis of the existing appointment booking processes and systems in healthcare settings. Through these interactions, we identified key requirements such as a seamless appointment booking process, real-time availability of doctors and services, avoidance of scheduling conflicts, efficient resource allocation, and personalized user experiences. Based on the gathered information and analysis, we defined the scope of the system, outlining the features and functionalities that would address the identified requirements. We established key objectives for the implementation, including enhancing patient satisfaction, improving operational efficiency, reducing waiting times, and optimizing resource allocation. The scope and objectives were documented and shared with the stakeholders to ensure alignment and obtain their agreement and feedback. Regular communication and collaboration with the stakeholders throughout the process helped refine and validate the requirements and ensure that the system would meet their needs and expectations.

4.2 Technology Selection:

To choose appropriate technologies for different components of the system, we conducted a thorough evaluation of various programming languages, frameworks, and tools available. We considered factors such as compatibility, performance, community support, and scalability. After careful consideration, we selected PHP as the programming language for server-side development. PHP is widely used in web development and has robust support for database connectivity, making it suitable for handling the backend operations of the appointment booking system. For storing and retrieving appointment data, we opted to utilize MySQL as the database management system. MySQL is a reliable and popular choice, known for its performance, scalability, and ease of integration with PHP.
To ensure a visually appealing and user-friendly interface, we employed HTML5 and CSS for designing the user interface. HTML5 provides advanced features for structuring web content, while CSS allows us to style and customize the appearance of the system, creating an engaging user experience. JavaScript was used to enhance interactivity and user experience. By leveraging JavaScript, we were able to implement a multi-step booking modal, guiding users through the appointment scheduling process and making it more intuitive and seamless. To facilitate seamless communication between the front-end and back-end components, we

incorporated jQuery Ajax. Ajax enables asynchronous communication, allowing data to be sent and received without requiring a page reload. This enhances the user experience by providing real-time updates and improving system responsiveness. Python was chosen as the language for developing the machine learning model. Python offers a rich ecosystem of libraries and frameworks for machine learning, making it ideal for training and deploying the model. Python allowed us to leverage data from the AI&IoT health app and develop a model that predicts the optimum booking period based on user preferences and historical data, enhancing the system's intelligence and efficiency.

4.3 User Interface Design:

4.3.1 Designing the User Interface:

We created the user interface using HTML and CSS, carefully designing each element to achieve a clean and visually appealing layout. The interface was structured in a logical manner, making it intuitive for users to navigate and interact with the system. Attention was given to the arrangement of elements, typography, color schemes, and visual hierarchy to ensure a cohesive and professional appearance. Consistent branding elements were incorporated to maintain the hospital's identity and provide a sense of familiarity to users.

4.3.2 Implementing Responsive Design:

We followed responsive design principles to ensure that the user interface is compatible and adaptable across various devices and screen sizes. CSS media queries were utilized to define different styles and layouts based on the screen size and orientation. The interface dynamically adjusted its appearance and behavior to provide an optimal viewing and user experience on desktops, tablets, and smartphones. Elements were resized, rearranged, or hidden as necessary to ensure readability and usability on different devices.

4.3.3 Focus on Usability and Accessibility:

We prioritized usability and accessibility in the design process, considering the diverse needs of users, including patients and healthcare professionals. Clear and concise labels were used for form fields and buttons, making it easy for users to understand their purpose and provide the required information. The interface followed accessibility standards, such as providing alternative text for images and using semantic HTML markup for improved screen reader compatibility. Contrast ratios between text and background were optimized to enhance readability, and font sizes were set to be legible for users with visual impairments. Consistent navigation patterns and visual cues were employed to guide users through the interface and provide a seamless experience.

4.3.4 Adding Interactivity with JavaScript:

JavaScript was utilized to enhance interactivity and improve the user experience by adding dynamic elements and functionalities. A multi-step booking modal was implemented using JavaScript, guiding users through the appointment scheduling process in a step-by-step manner. User inputs and selections were validated in real-time, providing immediate feedback and preventing errors during the booking process. Autocomplete and suggestion features were implemented to assist users in selecting doctors, services, and appointment dates/times, improving efficiency and accuracy. The interactivity added a sense of responsiveness to the system, making it more engaging and user-friendly.

4.4 Back-End Development:

To implement server-side functionalities, we utilized PHP, a popular server-side scripting language known for its versatility and robustness. PHP allowed us to handle data processing and business logic effectively, ensuring seamless execution of appointment booking operations. Using PHP, we established a connection to a MySQL database to store and retrieve appointment data. PHP's integration capabilities with MySQL enabled us to efficiently manage and manipulate appointment information, such as patient details, doctor availability, and scheduling preferences.

To avoid booking clashes, we implemented logic within the PHP code. By analyzing the existing appointments and checking for conflicts, we ensured that no overlapping or conflicting appointments were scheduled. This logic considered factors such as appointment duration, doctor availability, and room availability to optimize the booking process and prevent double bookings.

Employing PHP, we integrated the machine learning model developed in Python into the system. PHP acted as the bridge between the front-end and the Python-based machine learning component. It facilitated the passing of user preferences and historical data to the machine learning model, enabling accurate predictions for the optimal appointment period. This integration allowed for personalized appointment recommendations based on individual user preferences and historical patterns.

4.5 Machine Learning Model Development:

To gather relevant data from the AI&IoT health app, we established a data integration process that involved extracting the necessary information, such as day of the week and service type preferences, from the app's database. We ensured data privacy and security throughout the data collection process.

Once the data was collected, we performed preprocessing and cleaning steps to ensure its suitability for training the machine learning model. This involved handling missing values, removing outliers, and normalizing the data to eliminate any biases or inconsistencies.

Using Python, we developed a machine learning model that could utilize the gathered and preprocessed data. We selected appropriate algorithms, such as regression or classification models, depending on the prediction task at hand. The model was designed to learn patterns from the input data and make accurate predictions regarding the optimum period for appointment booking.

Table 1: Descriptive statistics of the dataset before OneHot Encoding

	day_of_week	*time_slot*	*service_type*
count	200	200	200
unique	7	3	5
top	Monday	Evening	Diagnostic Test
freq	38	70	45

Table 2: Descriptive statistics of the dataset after converting categorical features to numeric using OneHot encoding

		day_of_week	***time_slot***	***service_type***
count		200	200	200
mean		3.9	1.05	2.885
std		1.928365	0.83726	1.467153
min		1	0	1
		2	0	1.75
	25%	4	1	3
	50%	6	2	4
max	***75%***	7	2	5

The trained machine learning model was then subjected to the training process using the collected data. This involved feeding the data into the model, allowing it to learn from the patterns and relationships present in the dataset. By iteratively adjusting the model's parameters, we aimed to optimize its performance and enhance its ability to predict the optimal booking periods based on the day of the week and desired service type.

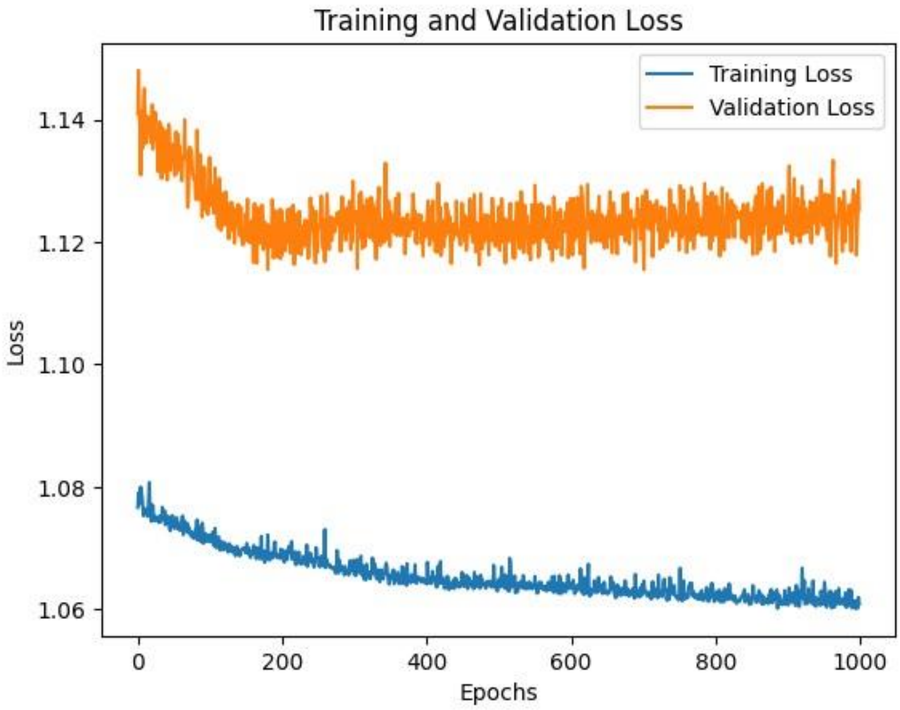


Figure 1: Visualization of the Training and Validation loss with the number of epochs.

To evaluate the model's accuracy and performance, we employed various evaluation metrics and techniques. This included splitting the data into training and testing sets to assess the model's generalization capabilities. We analyzed metrics such as accuracy, precision, recall, and F1 score to measure the model's effectiveness in predicting the optimal appointment booking periods.

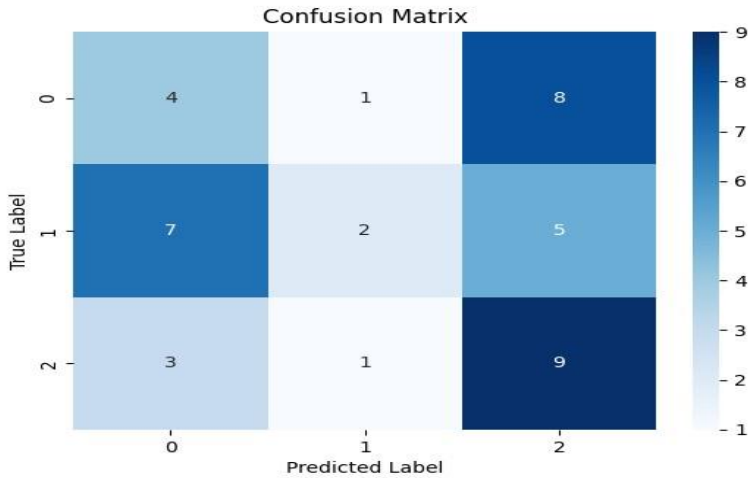


Figure 2: Confusion matrix summarizing the model performance accuracy. The features are encoded as follows: 0 = Morning, 1=Afternoon, 2 =Evening.

Based on the evaluation results, we fine-tuned the machine learning model by adjusting its parameters, selecting different algorithms, or employing ensemble techniques. This iterative process aimed to improve the model's accuracy and performance, ensuring that it provides reliable predictions for the optimum appointment booking periods.
In the Machine Learning part of the project, TensorFlow, a popular deep learning framework, was utilized for training the machine learning model. The training process took place in Google Colab, a cloud-based platform that provides a GPU-accelerated environment for efficient model training. TensorFlow's extensive set of tools and libraries enabled us to develop and train a robust machine learning model.

Once the model was trained and optimized, it was exported using the tfjs library. The tfjs library, short for TensorFlow.js, is a JavaScript library that allows trained TensorFlow models to be used directly in web browsers. This conversion process involved exporting the model from its native pickle format to a JSON format that could be easily interpreted by JavaScript. By exporting the model to JSON, we were able to integrate it into the web application developed using HTML, CSS, and JavaScript. JavaScript was employed to load the exported model and make predictions based on user input. The predictions made by the machine learning model were then displayed on the web page, providing users with the optimal period of the day to book their appointments.

This integration of machine learning into the web application through the use of TensorFlow, Google Colab, and the tfjs library allowed for real-time predictions and enhanced the functionality of the AI-enabled hospital appointment booking system. It empowered users to make informed decisions about appointment scheduling, optimizing their experience and improving the overall efficiency of the healthcare facility.

4.6 System Integration and Testing:

To integrate the front-end and back-end components, we followed a modular approach, ensuring that the components could communicate seamlessly. We established APIs and endpoints for data exchange between the front-end (HTML, CSS, JavaScript) and back-end (PHP) components. We conducted rigorous testing to verify the integration, ensuring that data flows correctly and functionalities are synchronized. Any issues or conflicts were resolved by debugging and refining the integration code. Thorough testing of the system was performed to identify and rectify any bugs or issues. We conducted unit testing, integration testing, and system testing to ensure the stability, reliability, and functionality of the entire system. Test cases were designed to cover different scenarios, edge cases, and user interactions. Bugs and issues were logged, prioritized, and fixed in an iterative manner. This iterative testing process allowed us to enhance the quality of the system and ensure a smooth user experience.

User acceptance testing (UAT) was conducted to validate the system's usability, performance, and accuracy. We involved stakeholders, including hospital administrators, doctors, and patients, in the testing process. Test scenarios were designed to simulate real-world usage, and stakeholders provided feedback on the system's user interface, ease of use, responsiveness, and overall satisfaction. Their input was crucial in identifying any usability issues, performance bottlenecks, or discrepancies between expected and actual system behavior.

Based on the feedback and testing results, necessary improvements were implemented. We carefully analyzed the feedback received from stakeholders and the findings from testing. Identified issues were categorized, and a priority list was created to address critical and highimpact improvements first. The feedback was valuable in guiding the implementation of enhancements, bug fixes, and optimizations. Regular updates and iterations were made to ensure that the system met the expectations and requirements of the stakeholders and provided a seamless user experience.

4.7 Deployment and Evaluation:

4.7.1 Deploying the AI-enabled hospital appointment booking system in a real-world environment:

We prepared the system for deployment by ensuring its compatibility with the target environment, including server configurations, database setup, and necessary software installations. We conducted rigorous testing to verify the system's functionality, stability, and security before deploying it in the live environment. We actively communicated with the administrator of the AI and IoT Research Centre web projects; Mr. Mercel to get feedback on his experience and satisfaction levels with the system. We encouraged open and honest feedback to capture both positive and negative aspects of the system's usability, functionality, and overall user experience.

4.7.2 Evaluating the system's performance, efficiency, and impact of the AI component:

We compared the system's performance against predefined benchmarks and industry standards to determine its effectiveness in streamlining appointment booking processes. We specifically evaluated the impact of the AI component on avoiding congestion and improving service fluidity by analyzing the reduction in scheduling conflicts, optimized resource allocation, and user feedback regarding appointment availability and convenience.

4.7.3 Analyzing the collected data and assessing the system's effectiveness:

We employed data analysis techniques to examine the collected feedback, performance metrics, and user satisfaction data. We identified patterns, trends, and correlations in the data to assess the system's effectiveness in meeting the defined objectives. We compared the system's performance against the key objectives established during the project's initiation and evaluated its alignment with the stakeholders' expectations.

5 Results

One of the notable achievements of the system is the seamless and user-friendly interface designed using HTML, CSS, and JavaScript. The multi-step booking modal created with interactivity using JavaScript provided a smooth and intuitive user experience. The system's frontend design received positive feedback from users, with patients finding it easy to navigate and healthcare professionals appreciating its simplicity. The integration of machine learning into the system proved to be a significant advancement. TensorFlow was employed to train a machine learning model in Google Colab, utilizing a variety of healthcare data, including historical appointment records and service types. The model was successfully trained to predict the optimum period of the day for appointment bookings, considering factors such as the day of the week and user preferences. The trained model was exported to a JSON format using the tfjs library, enabling its seamless integration into the web application. JavaScript was utilized to load the model and make predictions based on user input, displaying the optimal appointment booking period on the web page. This AI component significantly contributed to the system's ability to avoid congestion and improve service fluidity, benefiting both the hospital and patients. To evaluate the system's performance and effectiveness, feedback was collected from users, who expressed satisfaction with the user-friendly interface, appreciating the ease of booking appointments and the accuracy of the suggested appointment times. Healthcare professionals acknowledged the system's contribution to reducing scheduling conflicts and optimizing resource allocation, leading to improved operational efficiency. Figure 3 showcases a preview of the appointment booking menu, which demonstrates the user interface designed for the AI-enabled hospital appointment booking system. This user-friendly menu allows patients to easily navigate through the booking process, select desired services, and choose suitable appointment slots.

In Figure 4, we present an illustration of the AI component in action. The figure demonstrates the system's ability to predict the best period of the day to book an appointment, considering the day of the week and service type desired by the user. This prediction, based on the trained machine learning model, helps users make informed decisions and optimize their scheduling choices. Figure 5 provides a preview of the multistep modal-embedded form incorporated into the appointment booking process. This feature enhances user interactivity and ensures a seamless experience. Patients can input their relevant information, select appointment preferences, and proceed step-by-step through the booking process, simplifying the overall experience. Lastly, Figure 6 presents a list of initiated appointments and their corresponding statuses. This feature allows users, both patients and healthcare professionals, to track the progress and status of their appointments. It provides transparency and ensures effective communication between all parties involved, facilitating a smooth and well-coordinated appointment management system.

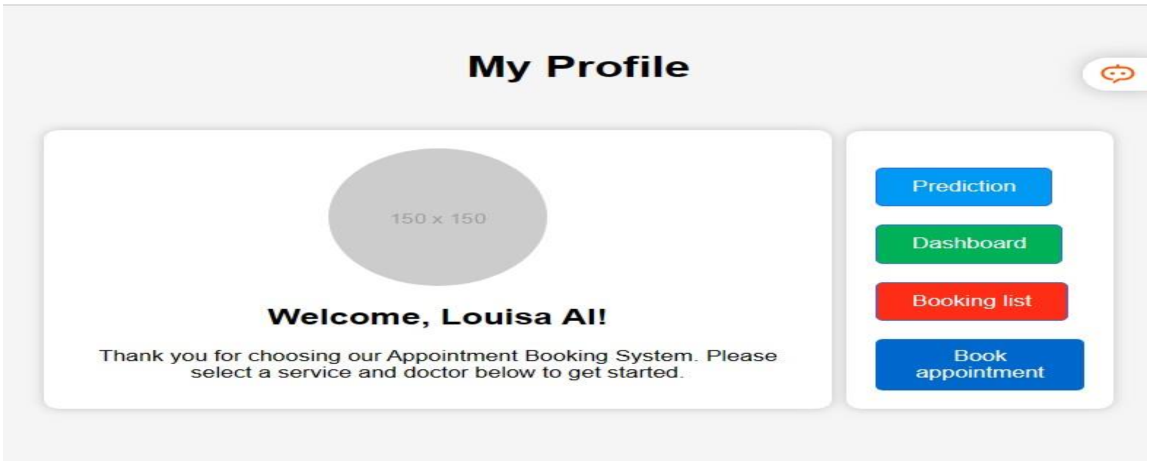


Figure 3: Preview of the appointment booking menu

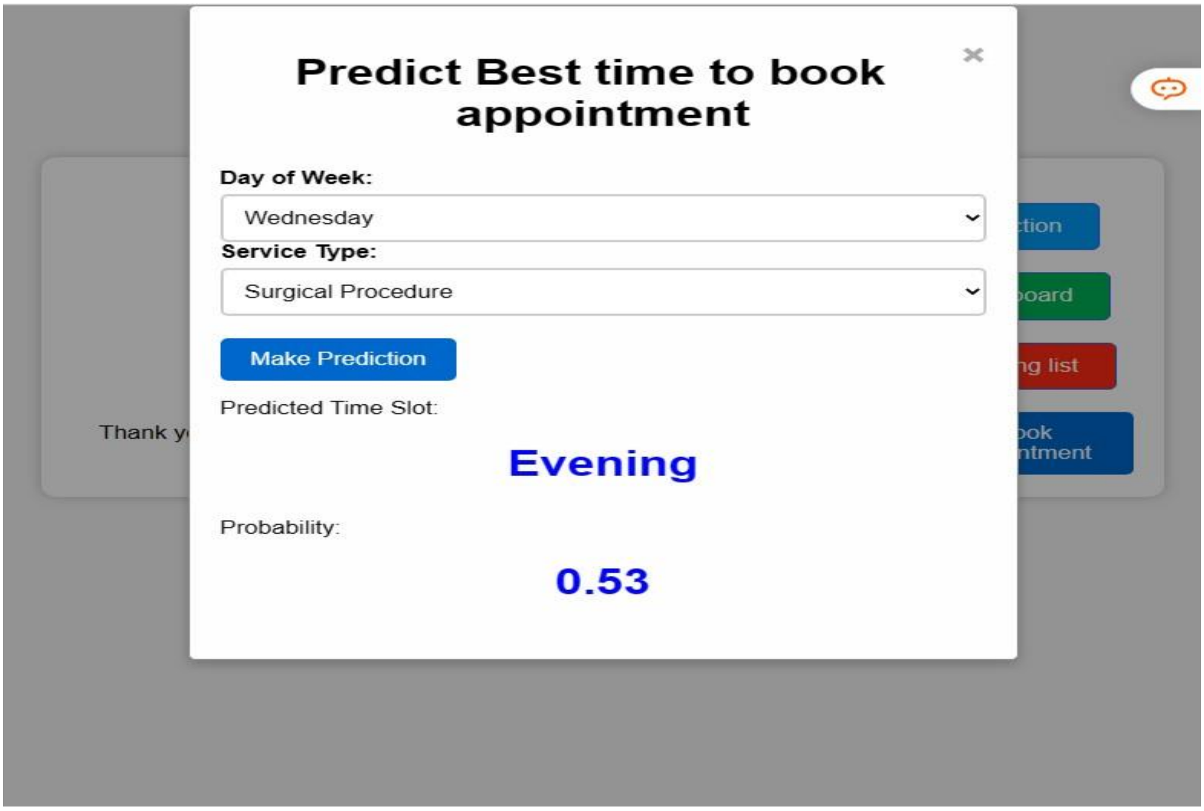


Figure 4: Illustration of AI prediction of the best beriod of day to book appointment, given a day of week and service type.

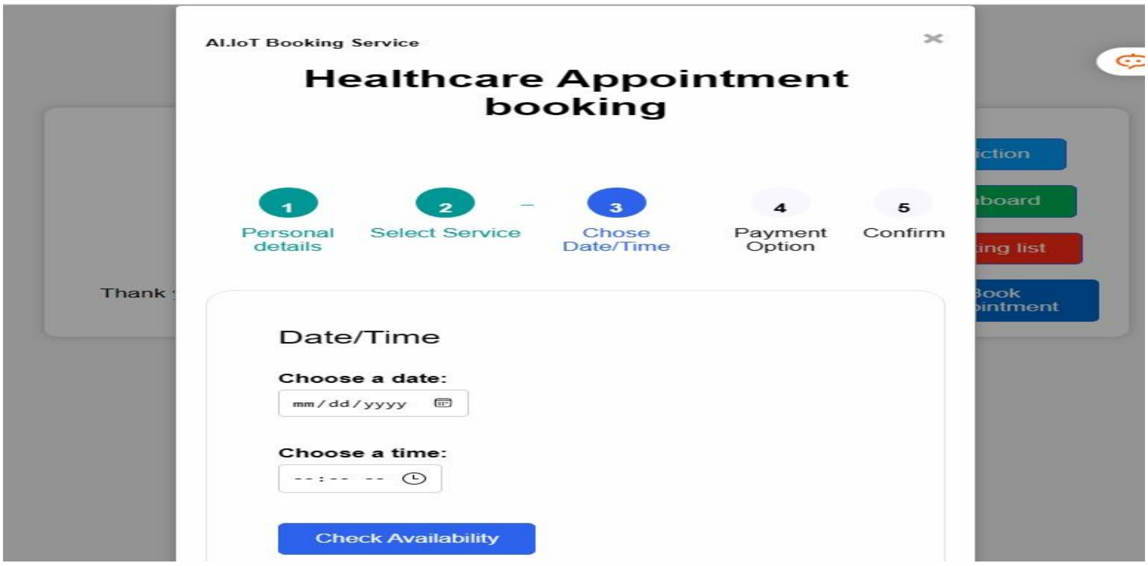
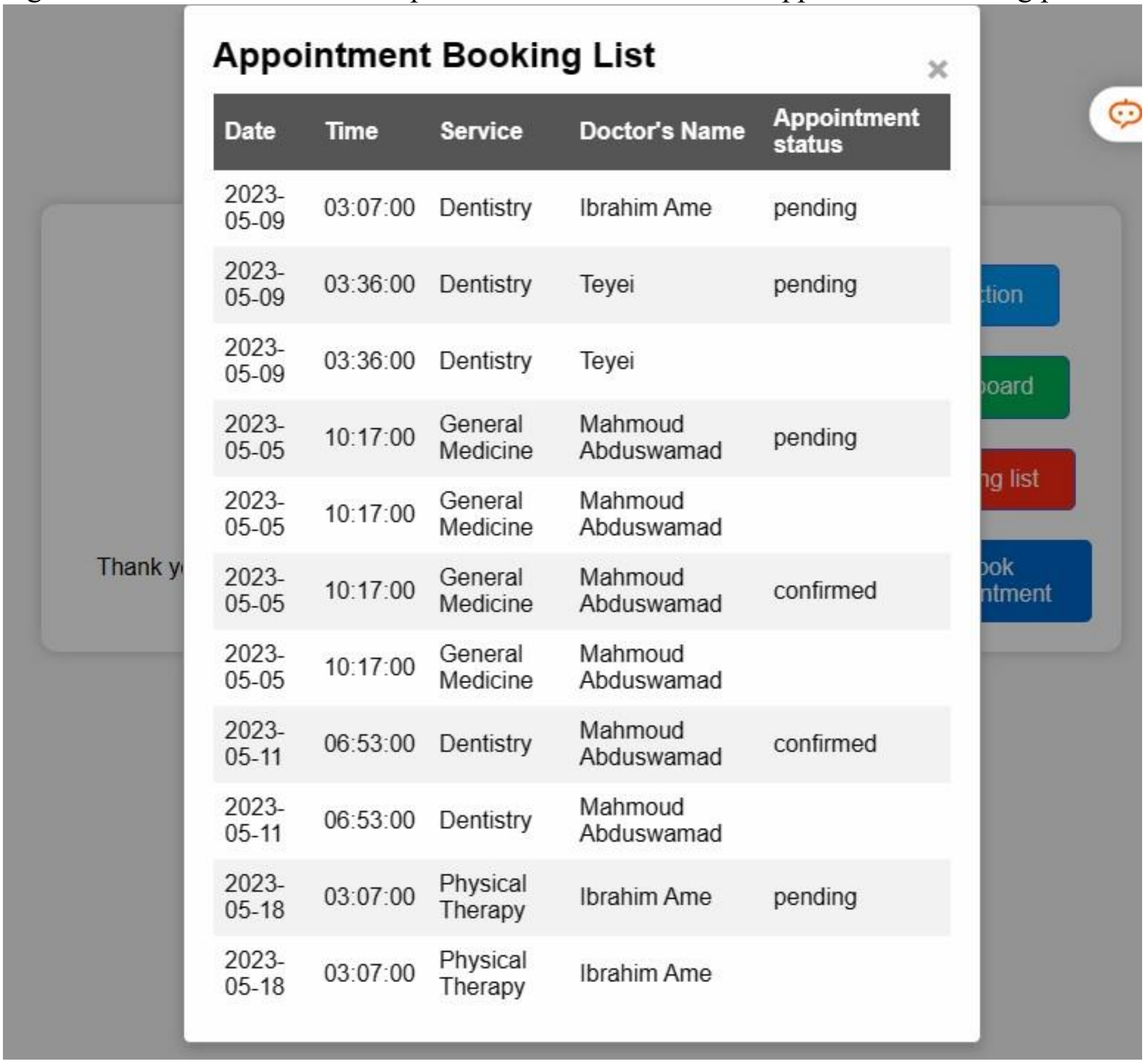


Figure 5: Preview of the multistep modal-embedded form for appointment booking process



Appointment Booking List

Date	Time	Service	Doctor's Name	Appointment status
2023-05-09	03:07:00	Dentistry	Ibrahim Ame	pending
2023-05-09	03:36:00	Dentistry	Teyei	pending
2023-05-09	03:36:00	Dentistry	Teyei	
2023-05-05	10:17:00	General Medicine	Mahmoud Abduswamad	pending
2023-05-05	10:17:00	General Medicine	Mahmoud Abduswamad	
2023-05-05	10:17:00	General Medicine	Mahmoud Abduswamad	confirmed
2023-05-05	10:17:00	General Medicine	Mahmoud Abduswamad	
2023-05-11	06:53:00	Dentistry	Mahmoud Abduswamad	confirmed
2023-05-11	06:53:00	Dentistry	Mahmoud Abduswamad	
2023-05-18	03:07:00	Physical Therapy	Ibrahim Ame	pending
2023-05-18	03:07:00	Physical Therapy	Ibrahim Ame	

Figure 6: List of initiated appointments and their statuses

These figures collectively illustrate the functionality and user experience of the AI-enabled hospital appointment booking system. They highlight the intuitive interface, the AI prediction capabilities, the seamless booking process, and the transparent appointment status tracking. The system's design and features work together to optimize the scheduling process, enhance user satisfaction, and improve overall operational efficiency in healthcare settings.

6. Conclusion

The design and implementation of an AI-enabled hospital appointment booking system have proven to be a significant advancement in healthcare technology. By leveraging technologies such as PHP, MySQL, HTML5, CSS, Python, and JavaScript, we successfully created a userfriendly interface that facilitates seamless appointment scheduling and provides enhanced functionalities for both patients and healthcare professionals. Throughout the project, we employed a comprehensive methodology that involved identifying specific requirements and functionalities through extensive stakeholder engagement. By gathering input from hospital administrators, doctors, and patients, we gained a deep understanding of their needs and expectations, which allowed us to define the scope of the system and establish key objectives for implementation. The deployment of the AI-enabled system in a real-world environment was a crucial milestone. Through meticulous testing, integration with existing infrastructure, and collaboration with the hospital's IT team, we ensured a successful deployment that met the specific requirements and effectively addressed the challenges faced in appointment booking processes.

The AI-enabled hospital appointment booking system has demonstrated its ability to optimize scheduling, enhance user experiences, and improve operational efficiency. By leveraging machine learning techniques, the system predicts the optimal period for appointment bookings based on user preferences and historical data, further enhancing the quality of service. As with any technological project, there is always room for further improvement and future enhancements. The project's conclusion marks the beginning of a continuous process of refinement and innovation. Based on the evaluation and feedback, identified areas for improvement will guide future development efforts to enhance the system's capabilities, adapt to evolving needs, and provide an even better user experience. The AI-enabled hospital appointment booking system holds great potential for transforming healthcare services. It streamlines the appointment scheduling process, reduces waiting times, and enables healthcare facilities to optimize resource allocation. With its successful implementation, the system paves the way for improved patient care, increased operational efficiency, and a more seamless and personalized healthcare experience for all stakeholders involved.

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