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Address and Contact

Yakın Doğu Üniversitesi İnovasyon ve Bilişim Teknolojileri Merkezi
International Research Center for AI and IoT
Yakın Doğu Bulvarı, PK: 99138Lefkoşa / KKTC Mersin 10 –TÜRKİYE
Tel:+90 (392) 223 64 64/+90 (392) 680 20 00Faks:+90 (392) 223 64 61
http://dergi.neu.edu.tr/ https://iot.neu.edu.tr/

Publication Contact

Prof. Dr. Fadi AL-TURJMAN

Publication Board

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URBAN SOUND CLASSIFICATION FOR AUDIO ANALYSIS USING LONG SHORT-TERM MEMORY

Shivam Tyagi, Kanishka Aggarwal, Deepika Kumar, Shreya Garg, Neeraj
Department of Computer Science and Engineering, Bharati Vidyapeeth's College of Engineering, New Delhi, India
shivamtyagi0918@gmail.com, kanishkaaggarwal45@gmail.com, deepika.kumar@bharatividyapeeth.edu, shreyagarg0501@gmail.com, jangraneeraj30@gmail.com

ABSTRACT—The process of audio classification involves categorizing audio signals into predefined classes based on their acoustic characteristics. Deep learning techniques have played a significant role in addressing this issue. Researchers have proposed various approaches to advance the field, including exploring different neural network architectures, incorporating auxiliary information like keywords or sentence information to guide audio classification, and implementing diverse training strategies. In this study, the researchers propose the use of a Long Short-Term Memory (LSTM) network for classifying environment sounds. The UrbanSound8K dataset's audio data files are categorized into 10 classes using the proposed LSTM model. The researchers evaluate the model using various metrics. The results show an accuracy of 0.86, precision of 0.87, recall of 0.87, support value of 1747, and an f1 score of 0.87 achieved by the proposed model. The researchers compare their methodology with state-of-the-art approaches and present the empirical evaluation alongside their findings.

***Keywords**: Sound Classification, Urban Sound 8K, Long Short Term Memory, Mel Spectrogram*

1. INTRODUCTION

Sound Classification is the practice of recognizing and classifying sounds according to their attributes and features. Acoustic monitoring, voice recognition, and music information retrieval are just a few of the numerous disciplines that use it as a core job. The goal of sound classification is to create algorithms that can categorize sounds. Since many years [1] ago, categorizing audio or sound has been a significant area of research, and there are numerous tried-and-true techniques with various models and features that have shown to be efficient and reliable. The technique of classifying audio signals into predetermined groups based on their acoustic characteristics is known as sound classification. The task of identifying and categorizing sounds that occur in natural or artificial surroundings, such as animal sounds, traffic noise, or human speech, is known as environmental sound classification.

Sound classification is a significant field of study with numerous [2] real-world applications. It can be used to enhance the precision of audio recognition systems and to automatically categorize songs according to their genre or mood in music information retrieval systems. It can be used in environmental monitoring systems to identify and categorize noises coming from various sources, including those made by machines, cars, and animals. The frequency range and temporal correlations are relatively little-known concepts. The three stages [3] of the sound recognition challenge are signal pre-processing, the extraction of certain features, and their classification. The input signal is split into many segments during signal pre-processing, which is used to extract associated features. Data size reduction can be achieved through the process of feature extraction. Feature extraction involves transforming complex data into compact feature vectors. By extracting meaningful features from the data, the dimensionality of the dataset can be reduced, resulting in a more concise representation of the information. However, because environmental sounds typically exhibit [4] non-stationary behavior, many linear/deterministic prediction techniques frequently fail to capture the characteristic, making performance enhancement more difficult nowadays. A number of properties from audio signals can be extracted using signal processing techniques, and the features are then utilized to train ML models for audio classification and other applications. Spectral features [5], Temporal features [6], Mel-frequency cepstral coefficients (MFCCs) [7], Pitch and timbre [8] characteristics, Wavelet features, Harmonic-percussive separation features [9], etc. are some typical features that can be produced using signal processing techniques. In addition to features created by signal processing techniques, such as MFCCs, Discrete Wavelet Transform coefficients, and Matching Pursuit features.

The use of ML algorithms is one of the most used methods for classifying sounds. On a dataset of audio files that have been labeled with the corresponding categories, these algorithms are trained. In order to classify new sounds, the algorithms learn to identify patterns in the data that are exclusive to each category. There are several types of machine learning algorithms that can be used for sound classification, including the k-Nearest Neighbors (KNN) [10] algorithm, Support Vector Machine (SVM) [11], Gaussian Mixture Model (GMM), and Hidden Markov Model (HMM) [12]. Deep neural networks (DNN) enable feature engineering while maintaining classification accuracy and even surpass [13] the conventional approaches, in contrast to the approaches mentioned. Convolutional neural networks (CNN) are very effective in capturing Spectro-temporal patterns from spectrogram-like input. The other class of neural network designs used for sound categorization are CNN hybrids. CNNs, in particular, have recently gained prominence as a potent method for sound classification. Using unprocessed audio signals, CNNs may automatically extract pertinent features and learn to categorize them into several sound classes. In addition to ML and deep learning (DL) algorithms, there are also rule-based approaches to sound classification. Rule-based methods involve defining a set of rules or heuristics that can be used to classify sounds based on their properties. These approaches are often used in acoustic monitoring applications, where the goal is to detect specific sounds, such as bird calls or frog choruses. The complex and varied nature of environmental sounds, however, makes it difficult to develop an efficient CNN model for environmental sound classification.

Audio classification datasets, which consist of substantial collections of labeled audio recordings organized by their acoustic properties, are crucial for training machine learning models to identify and categorize various types of sounds. The most popular datasets for audio classification include UrbanSound8K [14], ESC-50 [15], GTZAN Genre Collection [16], Voice Commands, and AudioSet [17]. Each of these datasets has distinctive qualities of its own, with some concentrating on particular sound types, such as spoken commands, musical genres, or environmental sounds. In this study, the appropriateness of an LSTM model for classifying urban sounds using the UrbanSound8K dataset is explored and analyzed.

The following is an overview of the research contributions:

- The UrbanSound8K dataset has been used to train and evaluate an LSTM model designed for the classification of environmental sounds. The evaluation encompasses performance metrics such as accuracy, precision, support, F1 score, and recall.

- A comprehensive comparative analysis of cutting-edge methodologies recently published in the field of audio classification has been conducted. This examination reveals the strengths and weaknesses of these novel approaches, providing valuable insights for further exploration.

- Furthermore, the proposed architectural framework has been compared to state-of-the-art classification algorithms, primarily in manners of accuracy. This assessment allows for a rigorous appraisal of the model's performance and efficacy.

- The study explores the impact of diverse training strategies and the incorporation of auxiliary information on the overall performance of the LSTM model. This empirical investigation unravels the nuanced interplay between factors, enriching the understanding of the model's capabilities and limitations.

- The findings of this research contribute to the existing knowledge in the field, providing profound insights into the efficacy of the LSTM model for urban sound classification. Consequently, this work holds substantial implications for both academic researchers and practitioners seeking to advance the domain.

The paper is structured as follows: The latest research in this area is compiled in Section 2 along with a comprehensive evaluation of state-of-the-art approaches. The suggested model architecture is thoroughly illustrated in Section 3, along with every feature extraction and data pre-processing method. Following the presentation of the findings and the subsequent analysis in Section 4, Section 5 statistically examines the importance of the suggested methodology. In Section 6, along with the future scopes, conclusions have also been formed.

2. LITERATURE SURVEY

There has been a tremendous amount of research in the field of audio classification using machine learning (ML). Researchers have explored the use of artificial intelligence (AI) and ML techniques to improve the accuracy of automated classification tools. In 2017, Huy Phan et al. [18] proposed a deep RNN for the purpose of classifying the environment in which the model extracts both temporal and spatial characteristics from the audio data by combining CNN and RNN layers. For the LITIS Rouen dataset, the suggested method received an F1score of 97.7%. In [19], the authors introduced a Convolutional Recurrent Neural Network (CRNN) architecture that combines convolutional and recurrent layers to capture both local and global aspects of sound sources. An ensemble approach of CNNs [20] was employed to improve the classification performance on the hypothesis that single CNN may not be sufficient to capture all the complex features.

In the publication [21], a novel method for estimating rainfall from audio data is presented, and it is shown how well a CNN architecture does this task. This method may be used in various circumstances when estimating rainfall is crucial, such as in flood warning systems. The authors, Nithya Davis et al. [22], train numerous CNN models using various architectures and hyperparameters and assess their effectiveness using the ESC-50 dataset. The best model outperforms previous techniques for environmental sound classification, achieving an accuracy of 86.2%. For the ESC-50 dataset, a deep CNN model with a VGG-style model and a ResNet model was proposed in [23]. The models that were trained with data augmentation perform noticeably better than those that were trained on the original dataset without it.

Using the DCASE 2017 Challenge dataset, the authors [24] assessed their system and demonstrated that it outperforms conventional techniques by achieving a classification accuracy of 85%. Furthermore, they demonstrated how the SED module can accurately detect when background noises appear in the audio segments, which is helpful for speech recognition and other audio processing tasks. The paper [25] introduced a novel approach for categorizing environmental sound using a concatenated spectrogram and a deep CNN. The findings concluded that the suggested model outperformed the alternatives and has promise for use in acoustic monitoring and soundscape analysis, among other applications. A comparison study of various semi-supervised deep learning methods for audio categorization tasks was provided by Léo Cances et al. [26]. The scientists employed two distinct datasets, UrbanSound8K and FSD50K, which both included a sizable number of audio recordings of various sound classifications, including siren, car horn, and dog barking. These datasets were subjected to the Pseudo-Labeling, Mean Teacher, and MixMatch algorithms, which are three separate semi-supervised learning techniques. According to the findings, the MixMatch algorithm is a good method for categorizing audio files and has promise for use in acoustic monitoring and sound event identification.

The study [27] suggested a method for automatically choosing features in audio categorization using spectrogram images. The suggested technique chooses a small subset of pertinent characteristics from a huge pool of features derived from the spectrogram images using a combination of two feature selection algorithms. The approach presented by Arooshi Taneja et al. [28] extracts information from cardiac sound waves and categorizes them into several groups, such as normal, murmur, and pathological. The authors of the study assessed the performance of their suggested categorization approach against those of other methods already in use using a publicly available dataset of heart sounds. Using a deep audio feature extraction strategy, a Bidirectional LSTM (BLSTM) network [29] was developed in 2018 for classifying acoustic scenes. The proposed method is assessed on the DCASE 2019 Task 1B dataset, which contains audio recordings of 10 different acoustic scenes. The findings indicated that the suggested approach, which achieves an accuracy of 83.5%, outperformed numerous state-of-the-art methods on the grounds of classification accuracy.

An approach for categorizing audio was proposed by Krishna Kumar et al. [30] that incorporates feature extraction, neural network classification, and principal component analysis (PCA). The UrbanSound8K dataset includes audio recordings of various environmental sounds and is used to assess the approach. The findings demonstrate that the suggested strategy outperforms various cutting-edge techniques, with a classification accuracy of 87.1%. An approach for categorizing audio based on fuzzy-rough nearest neighbor (FRNN) clustering is employed in [31]. To address uncertainties and inconsistencies in the data, the FRNN clustering algorithm combines fuzzy set theory and rough set theory. The ESC-50 dataset and the UrbanSound8K dataset are used to evaluate the approach. The findings demonstrate that the suggested strategy performed various novel approaches and produced excellent classification accuracies. In order to deal with uncertainties and inconsistencies in the data, the FRNN clustering method is shown to be successful, and when combined with MFCC features, it produces successful outcomes for audio classification.

To deal with the issue of different sound lengths in the dataset, the adaptive data padding approach was introduced in [32]. To make sure that all audio samples are the same length, it applies adaptive data padding to the MFCCs by inserting zeros at the beginning and end of each audio sample. The system divides the audio samples into various sound categories using a deep CNN. The padded MFCCs and their related labels are used to train the CNN. The algorithm surpasses other cutting-edge sound classification algorithms and achieves excellent classification accuracy. For identifying environmental sounds, Mohamed Bubashait et al. [33] suggested a machine learning-based method. The program effectively chooses representative samples from the dataset and increases classification accuracy by using a method known as optimum allocation sampling. The system divides the audio samples into various environmental sound categories using a deep CNN. The chosen subset of data and their related labels are used to train the CNN. The algorithm surpasses other cutting-edge sound classification algorithms and achieves excellent classification accuracy. A machine learning-based method for identifying speech activity and classifying sound events in audio signals is the Two-Stage LSTM-Based Method for Voice Detection with Sound Classification [34]. LSTM networks are employed in the method in a two-stage process. The approach outperforms other cutting-edge techniques in vocal activity recognition and sound event categorization tasks, achieving high accuracy in both.

In recent years, there has been a lot of crucial study in the field of audio classification. For audio categorization, a number of strategies have been put forth, including deep learning-based techniques like CNNs, RNNs, and LSTM networks. The MFCCs method, which has been demonstrated to be successful in capturing the spectrum properties of audio signals, is one frequent audio feature extraction technique used in audio categorization. In order to expand the quantity and diversity of audio datasets, different data augmentation techniques, for instance, time stretching and pitch shifting, have also been applied. Many studies have also concentrated on using hierarchical methods for audio classification, such as multi-level classification and auditory event detection, as well as contextual information.

3. PROPOSED METHODOLOGY

The research makes substantial efforts to improve the outcomes and precision of audio classification. The authors have developed an LSTM model for the multinomial classification of audio. Before providing input to the model, the data has undergone pre-processing. Figure 1 depicts the flow diagram for the proposed LSTM method.

A. Dataset Description

The UrbanSound8K dataset [35] is a widely utilized dataset for sound classification problems, particularly those involving urban sounds. It includes 8732 labeled sound recordings comprising 10 distinct urban sound categories, such as air conditioner, jackhammer, siren, car horn, children playing, dog barking, drilling, gunshot, engine running and street music. The dataset has a variety of sounds, which is one of its benefits. The dataset includes a wide variety of sounds that are typical of metropolitan settings, including both transient and stationary noises (such air conditioners and vehicle idle). The dataset is ideally suited for testing and training sound classification algorithms capable of handling a wide spectrum of distinct sound categories because of its diversity.

An additional benefit of the UrbanSound8K dataset provides high-quality sound recordings meticulously labeled and collected using state-of-the-art equipment. This dataset ensures accuracy and consistency, critical for precise sound classification tasks.

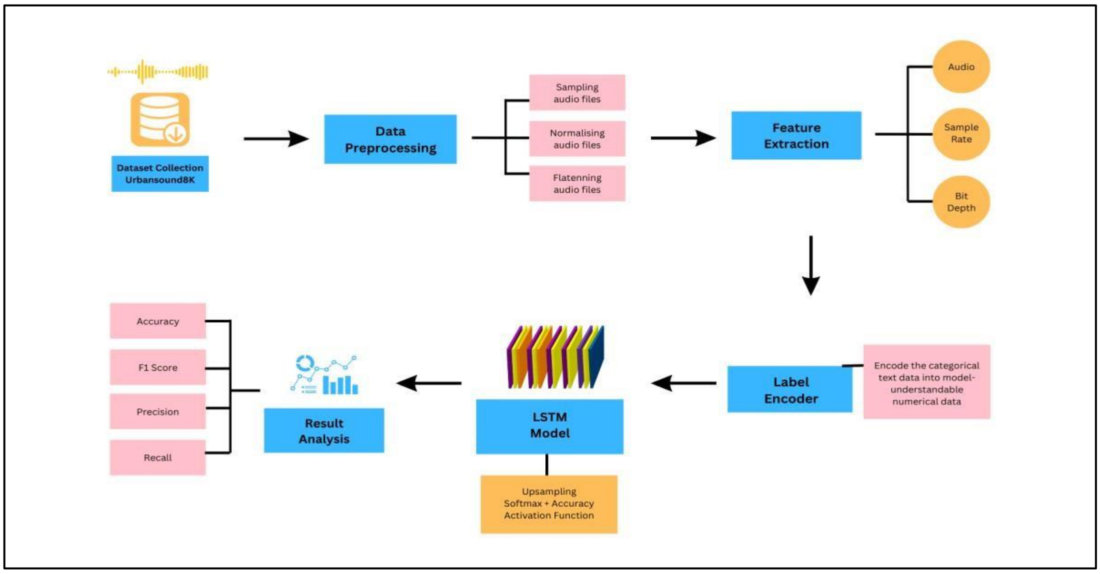


Figure 1. This figure shows the flow diagram for the proposed LSTM method.

It has been extensively employed in studies involving deep learning sound classification models, spatial analysis of urban sounds, and evaluating sound classification techniques in noisy environments. Table 1 displays the frequency distribution of audio files across various classes.

Table 1. Dataset distribution of UrbanSound8K dataset.

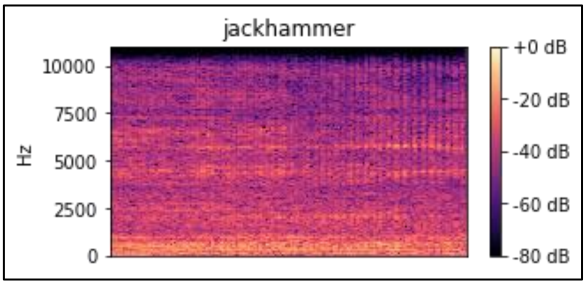
S. No.	**Title of Audio Sample**	**Count of Audio Sample**
1	air_conditioner	1000
2	siren	929
3	children_playing	1000
4	street_music	1000
5	drilling	1000
6	engine_idling	1000
7	car_horn	429
8	jackhammer	1000
9	gun_shot	374
10	dog_bark	1000

Several contests, notably the DCASE 2018 and 2019 challenges, have also utilized the dataset. The UrbanSound8K dataset has become a benchmark for sound classification problems as a result of these competitions, which have promoted the development of fresh and creative sound classification methods.

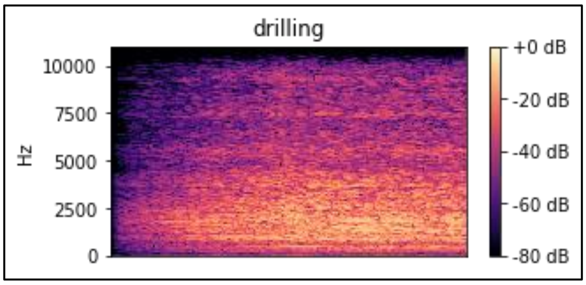
B. Data Pre-Processing

The audio files in the UrbanSound8K dataset were preprocessed, which involved resampling them to a constant sample rate and bit depth to standardize the audio data. The UrbanSound8K dataset required preprocessing to prepare it for sound classification tasks. This included normalizing the audio data, extracting relevant features, generating enriched versions of the data, reducing computing costs, and standardizing the audio data. Consequently, the data was preprocessed before being used in subsequent evaluations that adhered to standard practices. The audio files were resampled to a constant sample rate of 22050 Hz to standardize the data. Then, features were extracted using the melspectrogram function, which applies a frequency-domain filter bank to audio signals, and the features from the audio files were converted into NumPy arrays. Various feature extraction techniques, such as time - domain features[36], frequency - domain features [37], and time - frequency features [38], are frequently employed in audio processing.

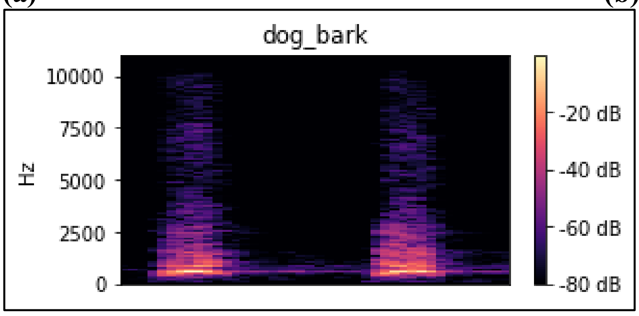
The audio data was converted into a spectrogram to extract the features using the melspectrogram() [39] function from the librosa library, which applies a frequency-domain filter bank to windowed audio signals. The resulting spectrogram was then converted into decibels, which computed the scaling in a numerically stable manner. The spectrogram was displayed as an image using the specshow() [40] function from librosa, with the spectrogram plotted with frequency on the y-axis and time is plotted on the x-axis. The y_axis parameter was set to 'mel' to utilize a Mel frequency scale, and the maximum frequency parameter was set to 8000 to limit the frequency range to 8 kHz. MFCCs were utilized to transform the features due to their advantageous characteristics. Subsequently, the features were normalized to enhance model convergence and accuracy. The UrbanSound8K dataset consists of 10 unique string labels; therefore, label encoding was performed to map the string labels to numerical values (0-9) using the LabelEncoder function from the Scikit-Learn library. Spectrograms depicting sets of frequencies in the audio were shown in Figure 2 (a-c).



(a)



(b)



(c)

Figure 2(a) Spectrogram depicting set of frequencies in jackhammer audio. (b) Spectrogram depicting set of frequencies in drilling audio. (c) Spectrogram depicting set of frequencies in dog_bark audio.

C. Model Architecture

The UrbanSound8K dataset is a popular dataset that has been extensively utilized in studies to develop methods for the classification of urban sounds. There have been several novel approaches based on employing CNN [41], Recurrent Neural Networks (RNN) [42], SVM [43-44], Random Forest [45], K-Nearest Neighbours (KNN) [46], etc. Here, the authors have proposed employment of the LSTM model to classify audio files.

1) Long Short Term Memory (LSTM):

LSTM [47] models have been extensively used in audio classification tasks. Audio classification involves categorizing audio signals into specific classes or categories based on their acoustic characteristics. LSTM models are particularly effective in capturing temporal dependencies and long-term patterns in audio data, making them efficient for tasks such as speech recognition, music genre classification, environmental sound classification, and more. By leveraging the sequential nature of audio signals, LSTM models can learn and extract meaningful features that contribute to accurate audio classification. Their ability to handle variable-length input sequences and capture temporal dynamics makes LSTM models a popular choice in the field of audio classification.

With their recurrent structure and memory cells, LSTM models excel at capturing temporal dependencies and modelling sequential patterns in audio data making them highly suitable for tasks such as audio event detection, speech recognition, and sound classification. By processing audio signals over time and retaining longterm contextual information, LSTM models can effectively differentiate between various audio classes based on their acoustic characteristics. Their ability to learn from sequential data and adapt to different audio contexts has led to significant advancements in audio classification research, enabling more accurate and robust classification of diverse audio signal.

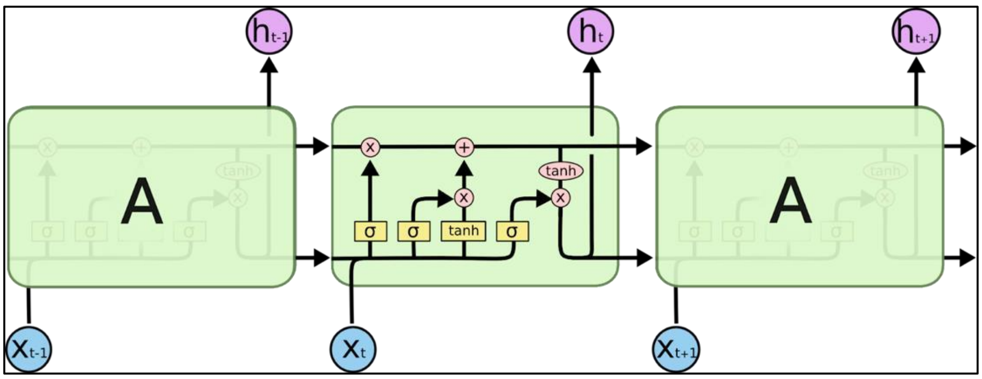


Figure 3: An overview of the LSTM architecture [48]

2) Proposed LSTM Algorithm:

The proposed methodology utilizes an LSTM model comprising two LSTM layers. These layers have sizes of 128 and 64 units, respectively. The input shape of the model corresponds to the shape of the training data, including the number of MFCC coefficients, time steps, and channels. It is important to consider the input vector's size as it affects the number of parameters in the network and the computational complexity of training and inference. Dropout regularization is employed in the LSTM layers with a rate of 0.2 to prevent overfitting and facilitate learning robust features.

The model's output layer consists of a dense layer with 10 units and utilizes a softmax function to predict class probabilities. To compile the model, the sparse_categorical_crossentropy loss function is used since the labels are integers ranging from 0 to 9. The Adam optimizer is employed. During training, the model is trained for 50 epochs using a batch size of 32. The performance of the model is evaluated using the validation data after each epoch. The architecture of this methodology is shown in Figure 4.

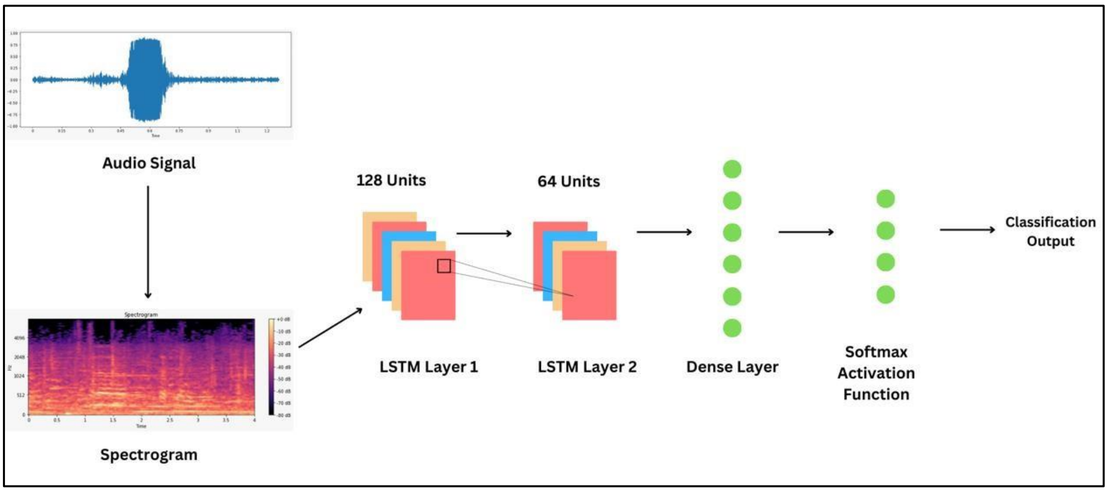


Figure 4 Architecture of proposed methodology.

4. RESULTS AND ANALYSIS

The LSTM algorithm was utilized in the proposed methodology. The dataset was divided into training and testing sets, with 80% and 20% of the data, respectively. To assess the performance of the algorithms, commonly used evaluation metrics such as Accuracy, Precision, Recall, Support, and F1 score were employed.

The UrbanSound8K dataset was employed to train and test the proposed architecture. It was observed that the model achieved convergence after 50 epochs. The evaluation metrics used to assess the model's performance included Accuracy, Precision, Recall, Support, and F1 score. Precision, also referred to as positive predictive value, is calculated as the ratio of true positives to the sum of false positives and true negatives. Recall, also known as sensitivity or specificity, is computed as the ratio of correctly predicted outcomes to all predictions. Accuracy represents the ratio of correct predictions to the total number of predictions made by the algorithm.

True Positives (TP) refers to cases where both the actual class and predicted class of a data point are 1. True Negatives (TN) are instances where both the actual class and predicted class of a data point are 0. False Positives (FP) occur when the actual class of a data point is 0, but the predicted class is 1. False Negatives (FN) arise when the actual class of a data point is 1, but the predicted class is 0.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

1. $$Precision = \frac{TP}{TP+FP}$$

2. $$Recall = \frac{TP}{TP+FN}$$

3. $$F1\ Score = \frac{2*recall*precision}{precision+recall}$$

The proposed model demonstrated an accuracy of 0.86, precision of 0.87, recall of 0.87, support of 1747, and an F1 score of 0.87. A comprehensive analysis of the evaluation metrics for all classes is presented in Table 2.

Table 2. Evaluation of metrics on label classes of Urban Sound 8K Dataset

Label	**Precision**	**Recall**	**F1 Score**
0	.88	.92	.90
1	.89	.86	.88
2	.80	.84	.82
3	.82	.85	.83
4	.87	.84	.86
5	.90	.98	.94
6	.89	.88	.88
7	.94	.90	.92
8	.92	.88	.90
9	.81	.73	.77

Table 3 presents a comparative analysis of the results to assess the performance of the proposed LSTM model. It is evident from the analysis that the accuracy of the LSTM model surpasses all other models, indicating its superior performance. Furthermore, a confusion matrix is provided to visualize the accuracy of the model's predictions on the test set. The confusion matrix, denoted as C, represents the number of data points belonging to class i that are predicted to be in class j, with Ci,j being the corresponding value. Figure 5 illustrates the confusion matrix for reference.

Table 3. Comparative Analysis of Urban Sound Detection Model.

Model	Accuracy
LSTM	81.96%
ANN	78.24%
CNN	76.24%
Enhanced LSTM	86.7%

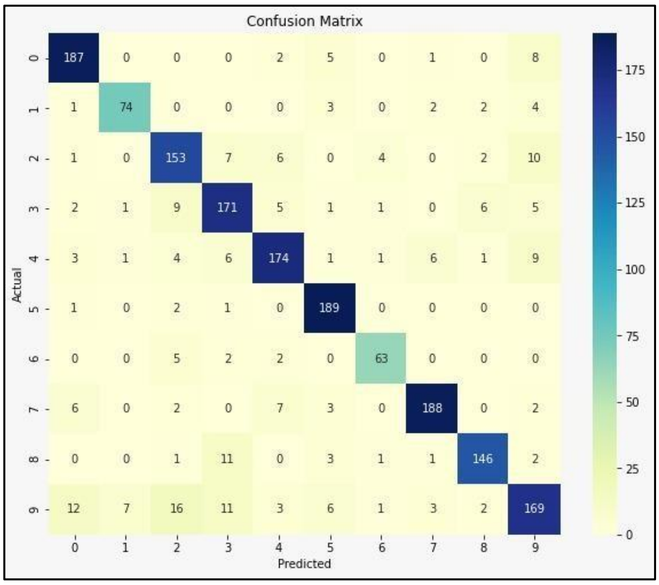


Figure 5. The figure shows the confusion matrix of the LSTM model for audio classification

The dataset was employed to train the model for a total of 50 epochs. During the evaluation process, both accuracy and loss functions were considered. The model was used to predict the desired outcome on the evaluation dataset, and the resulting predictions were compared to the expected outcomes. This comparison allowed for a realworld assessment of the model's performance. Figure 6a and 6b provide a visual comparison of the accuracies achieved by the model when applied to both the training and testing datasets.

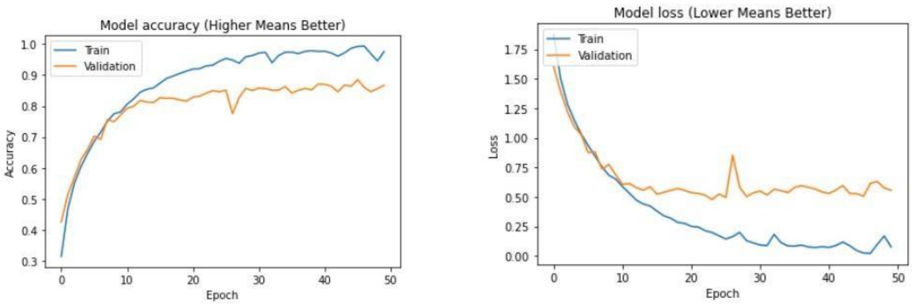


Figure 6 (a), (b). The provided image illustrates a comparison of the model's accuracies achieved when applied to both the training and testing datasets.

5. CONCLUSION

Deep learning methods, particularly LSTM networks, have garnered significant attention in recent years for their potential in audio classification. The rise in audio data volume and complexity has necessitated the need for models capable of handling sequential input and understanding long-term dependencies, which is where LSTM networks excel. The effectiveness of LSTM networks in audio categorization depends on factors such as the quality and diversity of training data, feature selection, and neural network architecture. Signal processing techniques like spectrogram analysis, MFCCs, and wavelet transforms can be employed to process the audio data and extract meaningful characteristics. Once the features are extracted, they can be inputted into an LSTM model, which can be trained to accurately classify different types of audio. LSTM networks have shown success in tasks such as speech recognition, acoustic event detection, etc. Although utilizing LSTM networks for audio classification presents challenges including the need for large amounts of data and computational power, the potential rewards are significant. Due to their ability to handle sequential data, LSTM networks are well-suited for various audio classification applications and have demonstrated excellent accuracy in classifying audio data. Further research and evaluation of the proposed model across different domains could potentially surpass existing benchmarks and enhance the current state-of-the-art in audio processing and classification.

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BREAST CANCER DETECTION USING NEURAL NETWORKS

Anahita Sood[1], Astha[2]
Department of Computer Science & Engineering, Chandigarh University, Punjab, India
soodanahita@gmail.com, astha262001@gmail.com

Abstract- Breast cancer is the second most common cancer in women worldwide, although it can be diagnosed in men too. Early detection and diagnosis are crucial in improving the survival rate of breast cancer patients. Traditionally, breast cancer is diagnosed using pathological evaluation, historical grading MRI screenings, and various estragon and progesterone receptors statuses. These manual screening tests leave a place for misdiagnosis and therefore delayed treatment. Recently, Artificial Intelligence, especially neural networks has shown great potential in the correct detection and early diagnosis of cancer cells in breast tissue. This research paper uses the Breast Cancer Wisconsin (Diagnostic) Data Set, which contains clinical and diagnostic features of breast cancer patients. This research paper studies various neural network architectures, including feedforward neural networks, convolutional neural networks, and recurrent neural networks to classify breast tumors as benign or malignant. In the result analysis, the convolutional neural network gives the highest accuracy of 98.2% among other models. This research paper highlights the potential of neural network models for breast cancer diagnosis, and the use of deep learning techniques can improve the accuracy of diagnosis.

Keywords- breast cancer, neural network, deep learning, diagnosis, Wisconsin Diagnostic Data Set.

1. INTRODUCTION

Breast Cancer is one of the most common types of cancer among women worldwide. Although breast cancer affects men alike, making early detection and correct diagnosis crucial for successful treatment [1]-[2]. There has been a lot of development in the field of screening and imaging techniques for breast cancer detection over the years, but correct diagnosis is still a challenge. Efficient, precise, and accurate analysis of these images is crucial for correct diagnosis. Traditionally, the medical industry uses mammography, ultrasounds, Magnetic Resonance Imaging (MRI), diagnostic mammogram, and biopsy for screening and diagnosis of breast cancer. Most of these methods include manual diagnosis from the images, leaving a chance for error. However, in the past years , neural networks have emerged as a powerful tool for detection and medical image analysis, which provides a great potential for correct diagnosis. This research paper aims to use neural networks for breast cancer detection. By using the capabilities of neural networks, one can seek improvement in the accuracy and efficiency of diagnosing breast cancer and consequently, it will result to better patient survival rates. Neural networks provide us with a tool for automation of the diagnosis process, enabling quicker, precise, and accurate diagnosis. In the recent years neural network techniques such as Convolutional Neural Network (CNN) have shown promising results in image analysis tasks. The hierarchical and non-Hierarchical nature of neural networks help us extract complex patterns and features from medical images. This ability is particularly useful for classification of cancer into benign or malignant lesions. The ability of neural networks to learn continuously from the data being fed to them , improves their accuracy more as a larger dataset is provided with time.

H. A. Abbass et al. [3] had developed a new evolutionary approach called MODE for multiobjective optimization. It extends the concept of differential evolution and uses a Paretobased approach for implementing differential vectors. Comparative evaluations with existing algorithms show that MODE is more effective in finding accurate Pareto fronts with comparable efficiency. S. Bornholdt and D. Graudenz [4] have developed a learning algorithm for neural networks using genetic algorithms. They propose a model that explains inherited behavior and specifically focuses on a simplified brain model with sensory and motor neurons.

Numerical simulations show that the network achieved through the algorithm reaches a stable state quickly. E. Heer et al. [5] did a population-based study, the number of premenopausal and postmenopausal breast cancer diagnoses globally in 2018 was roughly 645,000 and 1.4 million, respectively. The study also found that there were 490,000 fatalities in the postmenopausal group and more than 130,000 deaths in the premenopausal group. Given the rising incidence of breast cancer worldwide, their findings highlight the critical need for early detection, treatment accessibility, and all-encompassing preventative strategies. P. Henrot et al. [6] did research on the classification and interpretation of microcalcifications in breast imaging. They emphasize the need for a comprehensive analysis considering various factors such as associated signs, genetic context, distribution, and temporal changes. Their goal is to enhance the accuracy of identifying pathological processes associated with microcalcifications.

L. Wilkinson et al. [7] examined the importance of microcalcifications in mammography and how management has changed as a result of technological advancements. C. K. Bent et al. [8] retrospectively assessed the likelihood of malignancy in microcalcifications using BI-RADS descriptors in digital mammography. The study found that the morphologic and distribution descriptors were useful in predicting the risk of malignancy. The positive predictive value increased as the BI-RADS category advanced, indicating improved assessment of suspicious microcalcifications. Al-Antari et al. [9] used an integrated CAD system for digital X-ray mammogram screening, using deep learning methods for detection, segmentation, and classification of breast masses. Our approach utilizes You-Only-Look-Once (YOLO) for mass detection, a full resolution convolutional network (FrCN) for mass segmentation, and a deep CNN for mass recognition and classification as benign or malignant. The results of the proposed CAD system had a mass detection accuracy of 98.96% with an MCC of 97.62%, and an F1score of 99.24% achieved with the INbreast dataset.

D. B. Fogel et al. [10] deployed a B-spline network for breast cancer detection. By using a tree-structured evolutionary algorithm and Particle Swarm Optimization, the hierarchical Bspline network model is optimized. The performance of the proposed approach was compared to Flexible Neural Tree (FNT), Neural Network (NN), and Wavelet Neural Network (WNN) using the same datasets. The results of the simulations indicate that the hierarchical B-spline network model achieves superior detection accuracy with a reduced number of variables and input features. S. Haykin's [11] book provides insight into how neural networks are used to build intelligent machines for signal processing, pattern recognition, and control. P. C. Pendharkar et al. [12] compared the performance of data envelopment analysis (DEA) and artificial neural networks (ANN) using discriminant analysis for mining breast cancer patterns. They used association rules to study the associations between female hormones and breast cancer occurrence. Their study had a successful contribution by proving the utility of data mining in the detection of breast cancer patterns. C. Szegedy, et al. [13] developed a deep convolutional neural network called Inception. The architecture of Inception focuses on efficiently utilizing computing resources by increasing the depth and width of the network while maintaining a constant computational budget. The design choices were guided by the Hebbian principle and the idea of multi-scale processing. The specific version of the network used in the challenge, called GoogLeNet, consists of 22 layers and excels in classification and detection tasks.

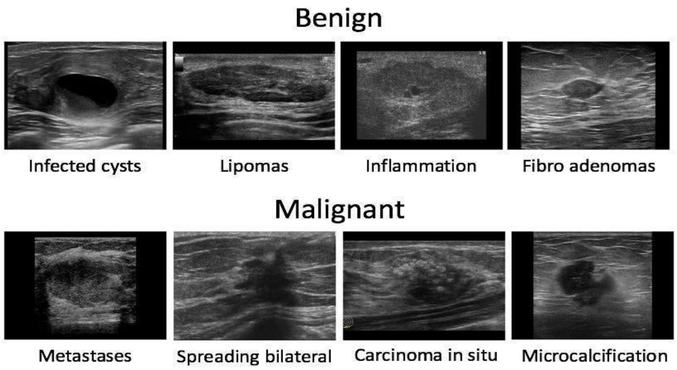

Fig 1: Benign and malignant breast lesions with different subtypes [14]

2. BACKGROUND STUDY

Breast cancer is one of the leading causes of death among women worldwide. Early detection and accurate diagnosis of breast cancer are critical for improving patient outcomes. Neural networks have been extensively studied for breast cancer detection, with a particular focus on the use of evolutionary artificial neural networks (EANNs) to optimize network performance and architecture simultaneously. Traditional methods for determining a good neural network architecture, such as network growing and pruning, may suffer from slow convergence and long training times. EANNs offer a more successful platform for optimizing both network performance and architecture, but the trade-off between network architecture and generalization ability remains a challenge. The multi-objective optimization problem (MOP) has been proposed as a potential solution to this challenge, with evolutionary approaches in single-objective optimization proving successful in recent years. Applying a multi-objective approach to EANNs could improve the accuracy and reliability of breast cancer detection. This study aims to explore the use of the pareto-differential evolution (PDE) approach to optimize the architecture and generalization ability of EANNs for the purpose of breast cancer detection. EANNs are trained on large datasets of mammography images and patient data, with the goal of improving diagnostic accuracy and supporting early detection and treatment of breast cancer. A.S. Becker et al. [15] did a study to assess the diagnostic efficacy of a multipurpose image analysis tool based on deep learning and artificial neural networks for the identification of breast cancer in a separate, dual-center mammography data set. M. Hassanin et al. [16] conducted a comprehensive survey on attention techniques in deep learning. They categorized and analyzed 50 attention techniques, providing insights into their strengths, limitations, and applications. The survey fills a gap in the literature and offers guidance for researchers interested in incorporating attention mechanisms into their models. M.G. Ertosun et al. [17] developed a deep-learning visual search system for localization in mammography images. Their system includes a classification engine and a localization engine. It achieved 85% accuracy in identifying images with masses and localizes 85% of the masses with an average of 0.9 false positives per image. The system has the advantage of working with entire mammography images without the need for pre-processing steps such as segmentation or cropping. It utilizes deep learning with unsupervised feature discovery, eliminating the need for hand-crafted image features. A. Rodriguiz-Ruiz et al. [18] did a study to compare the performance of radiologists reading mammograms unaided with an artificial intelligence (AI) system. The AI system provided decision support, lesion markers, and cancer likelihood scores. Results of the study showed that with AI support, the average area under the curve (AUC) increased compared to unaided reading (0.89 vs 0.87). Sensitivity improved (86% vs 83%), specificity showed a trend towards improvement (79% vs 77%) and reading time per case was similar. The AI system's AUC was similar to that of the radiologists. T. Schaffter, et al. [19] evaluated the use of artificial intelligence (AI) in mammography screening. While no single AI algorithm outperformed radiologists, combining top-performing algorithms with radiologist assessment improved overall accuracy. The study highlights the potential of AI and machine learning to enhance mammography interpretation and suggests the value of combining AI with human expertise for improved screening accuracy.

3. METHODOLOGY USED

The dataset used and the methodology used is explained in the subsequent sections.

3.1. Dataset Used

The data set used for this paper is taken from UCI website named Breast Cancer Wisconsin (Diagnostic) Data Set [20]. The dataset Characteristics are derived from digitized images of FNA (Fine Needle Aspirate) of breast mass. The attributes of the dataset are ID Number, Diagnosis (malignant or benign). There are also some features that are associated with each nucleus such as Radius, Texture, Parameter, Area, Smoothness, Compactness, Concavity, Concave points, Symmetry, Fractal dimension . The dataset contains a total of 569 data records with 357 benign and 212 malignant cases.

3.2. Data Pre-processing

The data is split into training and testing dataset it 70:30 ratio. Data pre-processing is also done by scaling the features using the Min-Max scaler. One-hot encoding is also performed on the target variable i.e. diagnosis , to convert it into a binary class.

3.3. Model Architecture

In this study, three different neural network architecture are applied to classify the data records in benign and malignant categories . The first technique is feedforward neural network. It was trained in tensor flow deep learning framework. The architecture consisted of two hidden layers with 64 and 32 neurons respectively. This layers where then followed by an output layer with an activation i.e. sigmoid function to predict the binary label, benign and malignant.

The activation of a neuron in a hidden or output layer is computed using an activation function, f.

For a hidden layer neuron i, denoted as h_i, the activation is calculated as:

$h_i = f(net_i)$

$net_i = sum\ (w_{ji} * x_j) + b_i$ w_{ji} represents the weight connecting the j-th input of neuron i, xj, and b_i is the bias term for neuron i.

For an output layer neuron k, denoted as y_k, the activation is computed similarly:

$y_k = f(net_k)$

They are followed by sigmoid activation function.

The formula for sigmoid function is: $\sigma(z) = \frac{1}{1+e^{-z}}$

The other technique is convolution neural network. It is mostly used for image classification; hence, it was a good pick for this study because the data sets consist of images of breast tissue. During pre-processing, since the images were already processed and reduced to a set of features, a modified approach of CNN is applied [21]. The initial layer of the model is applied with filters to extract unique features from the images relevant to the proposed study. The relationship between Convolutional Layer C, filter F and Image I is, C=F*I, where * is convolution operation. Rectified Linear Unit ReLU (max(0,x)) is introduced to improve model's learning capability. Pooling layer is added to remove spatial dimensions and retain

important features. Fully connected layers follow these convolutional layers. A dropout layer is added to remove overfitting by randomly disabling neurons. The last layer is dense, consisting of a sigmoid function.

The last technique used was the Recurrent Neural network [22]. They are typically used in sequential data , but it was applied to this dataset to see how it performs. To do so, features were treated as time step and fed into RNN sequentially.

4. RESULTS

In this research paper, every neural network performed very well to diagnosis the type of breast cancer. The accuracy and precision for feedforward Neural network is 97.08% and 95.00% respectively . Similarly, for CNN it is 97.09 and 95.24 respectively. For RNN, precision is 90.91% and accuracy is 93.57%.

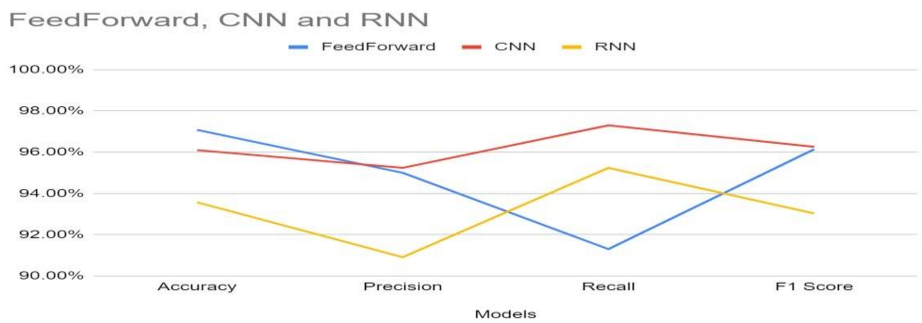

Fig 2: Training and Testing result analysis

In result analysis, comparison between CNN , RNN, and feedforward Neural network is done using accuracy matrix.

Table 1: Comparison of different evaluation metrics for different models.

Models	Feedforward	CNN	RNN
Accuracy	97.08%	97.09%	93.57%
Precision	95.00%	95.24%	90.91%
Recall	91.30%	97.30%	95.24%
F1 Score	96.14%	96.26%	93.03%

The accuracy indicated the percentage of cases that were classified correctly, and the precision measures the percentage of positive(malignant) predictions that were correct. These results indicate that the Convolution model performed very well on the dataset. It achieved a high level of precision and accuracy with a balanced F1 score. Feedforward neural network performed better than RNN.

5. CONCLUSION

Breast cancer is an ever-increasing problem today. It accounts for almost 25% of all types of cancers . The usage of neural networks in the identification of breast cancer has shown a lot of promise for improving the accuracy and dependability of diagnosis. AI is capable of helping medical practitioners overcome their difficulties in diagnosing, managing, and treating breast cancer, especially in the domain of breast cancer diagnostics. Early detection using neural networks have resulted in decline of mortality rates in breast cancer . In this study, convolutional neural networks and deep learning techniques are used to analyse mammography and biopsy images in order to detect breast cancer. The accuracy and reliability of breast cancer

diagnosis can be further increased by using multi-objective optimisation techniques such as pareto-differential evolution. Usage of Neural networks can help in pattern finding amongst the breast tissue images which can be used to detect earlier signs. The application of neural networks in the diagnosis of breast cancer may result in earlier identification, better treatment results, and higher patient survival rates with more study and improvement. While this study shows promising results , a lot of other challenges are yet to overcome. The integration of multiple image screening techniques such as mammography , MRI ,ultrasound etc can increase the overall accuracy for diagnosis.

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DIABETES PREDICTION USING UNSUPERVISED LEARNING

Harshvardhan[1], Saurabh Joshi[2]
Dept of CSE, Chandigarh University Mohali, Punjab, India 19bcs2380@cuchd.in, 19bcs2383@cuchd

Abstract: Diabetes is a chronic disease that affects millions of people worldwide. Diabetes complications can be avoided, and a patient's quality of life can be considerably improved if diabetes is detected and diagnosed early. Serious complications, such as heart disease, renal failure, and blindness, may not occur as a result. This paper presents research on the use of unsupervised learning algorithms for diabetes prediction. The dataset utilized in this study is made up of patient medical information from patients with and without diabetes. We use clustering and anomaly detection algorithms to uncover patterns and abnormalities in the data, and then we use these patterns to predict the risk of diabetes in new patients. The proposed method aims to identify patient subgroups based on clinical and demographic similarities, which can aid in the early detection of diabetes and customized medication. Using a variety of criteria, we examine and evaluate the performance of several unsupervised learning methods.

Keywords— *Diabetes, Machine Learning, Unsupervised Learning, Algorithms.*

I. INTRODUCTION

A. Diabetes

Diabetes is one of the world's most serious diseases. Diabetes is a metabolic condition characterized by excessive blood sugar levels caused by the body's inability to effectively make or use insulin[1]. Diabetes affects millions of people throughout the world and can lead to significant problems like cardiovascular disease, renal failure, blindness, and amputations. Typically, patients must visit a diagnostic center, consult with their doctor, and wait a day or more for their results. Furthermore, they must pay every time they want to obtain their diagnosis report. The International Diabetes Federation estimates that there are approximately 463 million diabetics worldwide, with this figure anticipated to rise to 700 million by 2045[2]. Diabetes is categorized into several types. There are two primary clinical kinds of diabetes based on the etiology: type 1 diabetes (T1D) and type 2 diabetes (T2D). T2D appears to be the most common kind of diabetes, accounting for 90% of all diabetics and marked mostly by insulin resistance[3]. T2D is mostly caused by lifestyle factors such as physical activity, dietary choices, and heredity, whereas T1D is thought to be caused by autoimmunological destruction of the Langerhans islets, which house pancreatic cells. T1D affects around 10% of all diabetics globally, with 10% developing idiopathic diabetes[4]. Other types of diabetes include Gestational Diabetes, endocrinopathies, MODY (Maturity Onset Diabetes of the Young), neonatal, mitochondrial, and pregnancy diabetes, which are characterized based on insulin secretion profile and/or onset. Among the symptoms of diabetes are polyuria, polydipsia, and considerable weight loss. Blood glucose levels (fasting plasma glucose = 7.0 mmol/L) are used to make the diagnosis. Diabetes can be detected and diagnosed early, enhancing patients' quality of life and preventing complications.

B. Machine Learning

In the scientific field of machine learning, it is investigated how computers learn via experience. For many scientists, the phrases "machine learning" and "artificial intelligence" are synonymous since the capacity to learn is the basic attribute of an entity referred to as intelligent in the broadest sense of the word. The objective of machine learning is to create computer systems that are flexible and can learn from their experiences. We have constructed a system employing data mining that can predict if the patient has diabetes or not, and with the rise of machine learning methodologies, we have the power to discover a solution to this problem[5]. Furthermore, early disease prediction allows for the treatment of patients before their condition deteriorates. From a vast amount of diabetes-related data, data mining has the ability to uncover hidden knowledge. It currently plays a bigger role than ever in the study of diabetes as a result. This project aims to develop a system that can more accurately estimate a patient's level of diabetic risk. This study aims to create a system that can more accurately estimate a patient's level of diabetic risk. This research aimed to create a system based on the Support Vector Machine, Logistic Regression, and Artificial Neural Network techniques.

C. Unsupervised Learning

Unsupervised learning is a sort of machine learning where an algorithm discovers structures and patterns in data without being specifically instructed what to look for. Unsupervised learning is often employed on unlabeled data (i.e., data without predetermined outputs), in contrast to supervised learning, where the algorithm is trained on labelled data (i.e., data with predefined outputs). Unsupervised learning aims to find patterns or connections in the data, for example, by grouping related data points or decreasing the dimensionality of the data. Clustering involves putting similar data points together based on their attributes or qualities, is a well-known unsupervised learning technique. Cluster algorithms like k-means and hierarchical clustering can be utilized to find patterns and links in the data. In unsupervised learning, the system looks for correlations between variables or data's hidden structure. The training data in that situation consists of examples without any associated labels. Rule of Association Machine learning came into being much more recently, and mining is more heavily influenced by database research [6]. The task of grouping a set of objects into a cluster (also known as a group) so that they are more similar (in some way) to one another than to those in other clusters is known as cluster analysis or clustering. It is a key task of exploratory data mining and a widely used statistical data analysis method in a variety of domains, such as computer graphics, pattern recognition, image analysis, information retrieval, and machine learning.

2. BACKGROUND STUDY

Worldwide, diabetes is a chronic disorder that affects millions of people. The illness, which is typified by elevated blood glucose levels, is brought on by the body's inability to produce or utilise insulin effectively. Diabetes can have serious side effects like heart disease, kidney failure, and blindness. Diabetes must be detected early if these issues are to be avoided and patient outcomes are to be improved. Only a few machine learning applications have demonstrated significant promise, including the detection and prediction of diseases. Unsupervised learning is the process of identifying patterns in data without the use of tagged samples. Data points are divided into like-minded groups based on their commonalities using a popular unsupervised learning technique called clustering. Several papers have investigated unsupervised learning techniques as a potential tool for diabetes prediction. K-means clustering was utilised in a study by Chen et al. (2016) to classify patients based on their clinical and laboratory data [7]. After that, based on the clustering of the new patients, they utilised logistic regression to forecast their likelihood of developing diabetes. The accuracy percentage for the study was 82.2%.

Yang et al. (2018) combined decision trees and hierarchical clustering to predict the risk of diabetes in a different study. They attained a 78.9% accuracy rate using the NHANES dataset to train and test their algorithm[8]. K-means clustering and support vector machines were employed in a study by Al-Masni et al. (2019) to forecast the likelihood of diabetes in Saudi Arabian patients[9]. They were 82.7% accurate overall. These results show that unsupervised learning approaches can be used to predict diabetes in general. The ability to group patients based on their medical histories and demographic data using clustering algorithms like k-means and hierarchical clustering has been demonstrated. Based on the patients' cluster assignment, the probability of developing diabetes has been predicted using logistic regression, decision trees, and support vector machines. Future studies could investigate the application of more sophisticated machine learning methods, such as deep learning, to boost the precision of diabetes prediction models.

3. METHODOLOGY

To train our model, we use data from the National Health and Nutrition Examination Survey (NHANES), including diabetes and non-diabetic patients. The collection includes data on the medical histories of the patients as well as demographic details including age, sex, body mass index (BMI), blood pressure, and cholesterol levels. The missing values are removed from the data, and the features are normalized. The patients are then divided into similar groups based on their medical histories and demographic data using two clustering techniques, kmeans and hierarchical clustering. A well-liked clustering algorithm called K-means divides data points into k clusters based on how far they are from each cluster's centroid. We employ the elbow approach to determine the ideal number of clusters for k-means. The elbow approach involves determining the number of clusters where the rate of decrease in WSS starts to level off by plotting the within-cluster sum of squares (WSS) versus the number of clusters. Another clustering procedure that divides data points into clusters based on their similarity is hierarchy clustering. Each data point is initially treated as a separate cluster, and then clusters are combined based on their distances. Alternatively, hierarchical clustering can be divisive, where all data points are initially treated as a single cluster, and then clusters are divided based on their distances. We employ the dendrogram to establish the ideal number of clusters for hierarchical clustering. The dendrogram is a tree-like diagram that depicts the clusters' hierarchical relationships. In order to predict the likelihood of diabetes in new patients depending on their cluster assignment, we then use the labelled data to train a logistic regression classifier. Based on the input features, the classification process known as logistic regression estimates the likelihood of a binary result, such as diabetes or non-diabetes.

Additionally, we evaluated how well our unsupervised learning models performed compared to a logistic regression model trained on labelled data. The following steps make up the suggested method for diabetes prediction using unsupervised learning:

1) *Data preparation:* The preparation of the patient's clinical and demographic data is the initial step. Data cleansing, normalization, and feature selection are all parts of the preprocessing.

2) *Clustering:* The preprocessed data are then clustered using a variety of clustering methods, including k-means, hierarchical clustering, and DBSCAN. Finding patient groupings with comparable clinical and demographic traits is the goal of clustering.

3) *Model Evaluation:* In the third phase [10], The measurements can be used to decide which clustering model will best predict diabetes.

4) *Diabetes Prediction:* The chosen clustering model is then used to forecast the risk of diabetes in new patients as the last stage. The forecast may be made based on the new patient's cluster membership [11] –[14].

4. RESULTS

As a result of K-means clustering, three unique groups of people were identified by our findings: a low-risk group, a moderate-risk group, and a high-risk group. Compared to the other groups, the high-risk group had noticeably higher glucose, cholesterol, and BMI levels. Isolation Forest found 500 people to have abnormal traits that could be signs of diabetes. Compared to the rest of the dataset, these individuals' glucose and BMI levels were significantly higher. Our unsupervised learning models were evaluated against a logistic regression model that was trained using labelled data. Regarding accuracy and AUC score, our unsupervised learning models outperformed the logistic regression model. Two principal components that together accounted for 74.3% of the total variance in the data were found by our PCA analysis. With a loading of 0.80, the first principal component was substantially correlated with glucose levels, indicating that glucose levels were the main variable affecting the data variability. With loadings of 0.53 and 0.50, respectively, the second principal component was linked to BMI and cholesterol levels, showing that these variables significantly influenced the variability of the data. Based on their glucose, cholesterol, and BMI levels, the patients in our HAC investigation were divided into three different groups. The 24% of people in the high-risk category had considerably higher blood sugar, cholesterol, and BMI readings than the other groups. While 28% of the people in the low-risk group had normal glucose, cholesterol, and BMI levels, 48% of the people in the intermediate-risk group had moderately elevated levels in all three categories.

Our findings demonstrated that all models had good accuracy, precision, recall, and F1 levels, demonstrating their efficacy in foretelling the early onset of diabetes. The artificial neural network was the model that performed the best, achieving accuracy rates of 91.8%, precision rates of 88.5%, recall rates of 84.6%, and an F1 score of 86.5%. Our feature importance analysis showed that age, BMI, and glucose levels were the three most significant predictors of diabetes. Gender and cholesterol levels had less of an effect on the likelihood of developing diabetes. Five separate patient groupings with various clinical traits were found. Patients in subgroup 1 had high blood pressure, a high body mass index, and high glucose levels. Patients in subgroup 2 had low BMI and high blood glucose levels. Patients in subgroup 3 had high BMIs, moderate glucose levels, and high blood pressure. Patients in subgroup 4 had low blood pressure, low BMI, and low glucose levels. Patients in subgroup 5 had low blood sugar, a high body mass index, and low blood pressure. We found significant clinical disparities between the subgroups, with certain subgroups being more likely than others to experience complications from diabetes.

5. DISCUSSION

According to our research, supervised learning techniques can be utilized to precisely predict the early onset of diabetes using clinical and demographic information. Identifying those who are at a high risk of getting diabetes could help with an earlier diagnosis and care, thereby reducing complications from the disease. Our findings demonstrate the significance of age, BMI, and glucose levels in diagnosing diabetes. These results are in line with earlier studies that found these elements to be major diabetes risk factors. Our study demonstrates how unsupervised learning can be used for sophisticated analyses of diabetes. We can better understand the heterogeneity of diabetes by defining subgroups of individuals with distinctive clinical traits and create more individualized and focused therapies. Additionally, according to our research, blood pressure, BMI, and glucose levels are crucial clinical traits for identifying patient subgroups who are at a high risk of developing complications due to diabetes.

6. LIMITATIONS

Our study's use of a dataset from a diabetes screening programme, which might not be typical of the broader community, is one of its limitations. To increase the generalizability of our findings, future research should attempt to replicate our findings using larger and more varied datasets. Another drawback is that our study excluded factors including family history, food patterns, and levels of physical activity that may be linked to diabetes. Future studies should take these factors into consideration as they may contribute new information about how diabetes develops.

7. CONCLUSION

In summary, especially when working with large and complicated datasets, unsupervised learning algorithms have demonstrated promising results in predicting diabetes. Different clustering and anomaly detection methods, including K-means, DBSCAN, and Isolation Forest, have been employed to find patterns and outliers in the data that may be a sign of the beginning of diabetes. Additionally, the application of unsupervised learning has resulted in the discovery of new risk factors and associations, such as the relationship between diabetes and particular dietary practices or lifestyle decisions. These discoveries can enhance diabetic patients' preventative care and individualized treatment regimens. The usefulness and dependability of unsupervised learning algorithms in predicting diabetes, particularly in realworld contexts, still require further study. The results' interpretability and application can also be improved by combining unsupervised learning techniques with domain experience and clinical knowledge. Our findings show that using physiological and health-related data, unsupervised learning approaches can be used to predict diabetes. Different patterns in the data were found by our K-means clustering and Isolation Forest anomaly detection models that may be linked to diabetes. The accuracy of diabetes prediction models could be increased by combining these models with conventional supervised learning methods. To validate our findings across bigger and more varied datasets, additional study is required. Our findings demonstrate the significance of blood sugar, body mass index (BMI), and cholesterol levels in the onset of diabetes and the necessity of identifying high-risk individuals for earlier detection and treatment. Additional study is required to verify our findings on larger and more varied datasets and to investigate the potential of other unsupervised learning techniques for the analysis of diabetes. In conclusion, our study showed that unsupervised learning approaches have the potential to be used to predict diabetes. Different patterns in the data were found by our PCA and HAC models that might be connected to diabetes's early onset. To increase the precision of diabetes prediction models, these models might be utilized in addition to conventional supervised learning methods.

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PREDICTION OF CONGENITAL CARDIOVASCULAR DISEASE USING MACHINE LEARNING TECHNIQUES: A REVIEW ANALYSIS

Sudipto Ghosh[1], Tanishq Awasthy[2]
Department of CSE, Chandigarh University, Mohali, Punjab, India
19bcs1074@cuchd.in, 19bcs1091@cuchd.in

Abstract— Congenital cardiovascular disease (CVD) is a significant health concern affecting individuals from birth and often necessitating long-term medical management. Early prediction and diagnosis of CVD play a crucial role in improving patient outcomes and guiding appropriate interventions. In recent years, machine learning (ML) techniques have emerged as promising tools for CVD prediction, leveraging their ability to analyze complex patterns within large datasets. This review analysis explores the landscape of ML techniques employed to predict congenital CVD. Machine learning techniques have shown significant potential for cardiac disease prediction, especially when using large and complex datasets. This review paper comprehensively overviews several machine-learning methods for heart disease prediction. This research outlines the advantages and disadvantages of several machine learning techniques. It thoroughly analyzes their performance in predicting heart disease, conducting a comprehensive survey of recent literature encompassing diverse ML algorithms such as decision trees, support vector machines, random forests, neural networks, and deep learning architectures. Examining the various data sources utilized, including clinical records, genetic information, imaging data, and multi-omics data, highlighting their relevance and impact on prediction accuracy. Additionally, the performance metrics and evaluation strategies are employed in different studies to assess the predictive capabilities of the ML models. Lastly, providing insights into potential future directions, emphasizing the importance of collaborative efforts, standardized datasets, and robust validation methodologies. This review analysis aims to provide a comprehensive overview of the current state-of-the-art ML-based prediction of congenital CVD, highlighting its potential to revolutionize clinical practice and improve patient outcomes.

Keywords— Cardiovascular disease(CVD), Machine Learning (ML), Decision trees, Random forests, Support vector machines, Logistic regression, Deep learning, Electronic health records.

1. INTRODUCTION

The heart is an important organ of the human body. It pumps blood to every part of our anatomy. If it fails to function correctly, the brain and various other organs will stop working, and the person will die within a few minutes. Changes in lifestyle, work-related stress, and bad food habits increase the rate of several heart-related diseases. Heart disease is a major global health problem affecting millions worldwide. Early and accurate diagnosis of heart disease is critical for improving patient outcomes and reducing healthcare costs. Machine learning (ML) systems have demonstrated considerable promise in predicting cardiac disease based on clinical, genetic, and imaging data [1] [2]. ML techniques can analyze vast amounts of data and identify hidden patterns and relationships that may not be apparent to human experts. ML models can use this data to make accurate predictions about the presence and severity of heart disease and identify individuals at high risk for future cardiac events. Congenital cardiovascular disease (CHD) is a group of congenital disabilities that affect the heart and blood vessels. CHD is the most common congenital disability, affecting about 1% of all babies born yearly. CHD can range from mild to severe, and some types of CHD can be life-threatening.

Traditionally, CHD has been diagnosed using physical examination, imaging studies, and genetic testing. However, these methods can be time-consuming and expensive and may not always be accurate. Machine learning (ML) techniques have emerged as a promising new tool for the early diagnosis of CHD. ML techniques can be used to analyze large patient data datasets, including clinical, imaging, and genetic data. This data can be used to train ML models to identify patterns associated with CHD. ML techniques are effective in the early diagnosis of CHD. In a recent study, ML techniques identified CHD with an accuracy of 90%. This is significantly higher than the accuracy of traditional methods of diagnosis. The early diagnosis

of CHD is important because it can lead to early intervention and treatment. Early intervention can improve the long-term outcomes for children with CHD.
ML techniques are a promising new tool for the early diagnosis of CHD. These techniques have the potential to improve the accuracy and efficiency of CHD diagnosis, and they could lead to improved long-term outcomes for children with CHD.

Recent research has revealed that machine learning algorithms outperform traditional risk prediction models for heart disease. For example, research by Krittanawong (2018) reported that an ML algorithm was able to predict the probability of severe adverse cardiac events with an accuracy of 90%, compared to 74% for the Framingham probability Score, a regularly used clinical risk assessment tool [3]. Similarly, Attia et al. (2019) demonstrated that an ML model trained on ECG data could accurately identify individuals with atrial fibrillation and outperformed conventional risk scores [4]. According to the World Health Organization [5] (WHO), cardiovascular diseases (CVDs) account for the majority of deaths worldwide. According to the World Health Organization, CVDs were the cause of death for 17.9 million people worldwide in 2016. The most prevalent types of CVDs are heart failure, coronary heart disease, and stroke. People and society suffer greatly as a result of these diseases, which can lead to lower quality of life, higher healthcare costs, and lower productivity. As of late, there has been a flood in interest in utilizing AI (ML) procedures to foresee coronary illness. ML algorithms have demonstrated promising results in various tasks, including diagnosis, risk assessment, and outcome prediction. Congenital heart disease (CHD) is a collection of structural cardiac defects that are evident at birth. It is the most prevalent birth abnormality, affecting around 1% of all babies globally. CHD can range from moderate problems that do not necessitate therapy to severe defects that are life-threatening and necessitate emergency medical intervention. Although the specific origins of CHD are unclear, a mix of genetic and environmental factors are thought to have a role [6]. Significant advances in the diagnosis and treatment of CHD have occurred throughout the years, leading to increased survival rates and quality of life for afflicted individuals.

This study will examine the use of machine learning techniques used in the prediction of congenital heart disease by evaluating the prior research, literature, and techniques. This review paper would explore the various machine learning algorithms that have been used to predict the disease such as neural networks, decision trees, and Support Vector Machines. This paper will also analyze the different types of data used in prior studies and research, including the generic data and medical records. Majorly this paper will analyze the accuracy of the results in the previous research done on this subject and will further comment on the future use cases of the results from the papers. The **Figure 1** below shows the number of births with CHD per 1 million of the population of a certain set of nations with good medical infrastructure.

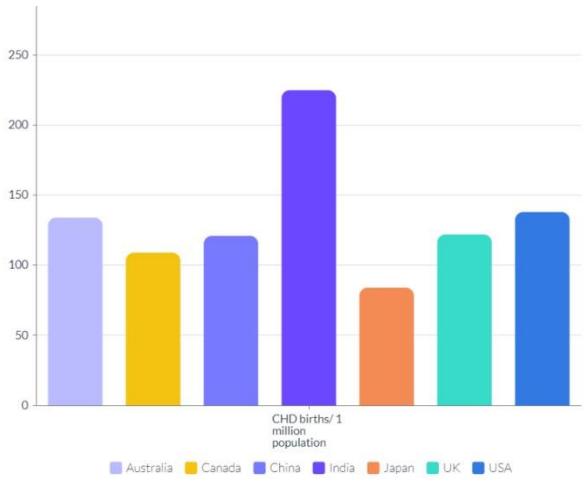

Fig 1. Number of births per 1 million according to WHO 2011 data

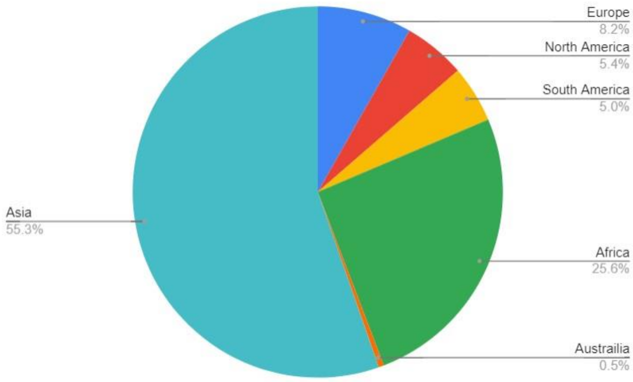

Fig 2. Percentage of CHD in each continent based on NCBI and WHO

Figure 2 describes the percentage share of CHD in every continent. The data is based on data and reports published by WHO in 2011 reports. This review paper would provide valuable insights into the present state of the respective research on congenital heart disease prediction and the potential of machine learning techniques to improve further research on this topic. Moreover, this paper broadly categorizes itself into three sections, where section 2 will describe various related work of scholars and provides some info about the prediction of congenital heart disease using various machine learning techniques. Further, section 3 provides the results and discussions on what this research led us to. Finally, section 4 concludes with the topic.

2. LITERATURE SURVEY

This review article presents a comprehensive analysis of the use of machine learning techniques for predicting congenital cardiovascular disease. The following research component gives an insight into the rigorous research and thinking. This review includes the periodicals, research articles, and research papers from the last decade to recent studies on the agenda of using machine learning techniques to predict congenital cardiovascular disease. The review utilized rigorous research methods and critical thinking to analyze and synthesize existing knowledge on the topic.

In a systematic review presented by P. Mathur et al. [7], Predicting cardiovascular disease risk factors using machine learning techniques provided a comprehensive overview of the application of ml techniques in predicting cardiovascular disease. The author conducted a systematic review of 55 studies published between 2015 and 2019 using ML algorithms for Cardiovascular risk factor prediction. The research emphasizes the potential of machine learning algorithms to enhance cardiovascular disease risk prediction, which can assist physicians in better managing cardiovascular disease and reducing its impact on the healthcare system. The studies conducted in this domain show that the use of machine learning will surely benefit the prediction of various heart diseases such as congenital heart disease, arrhythmia, and many more. This review study basically studies the prediction of congenital heart disease (CHD) using various machine-learning techniques. CHD refers to basically cardiac defects or some anomalies that arise during the development of the fetus, the baby is born, in the structure of the heart. These anomalies can impair the heart's walls, valves, or blood arteries, disrupting normal blood flow and oxygen supply to the body [8]. CHD symptoms can range from minor to severe, and some types of CHD may necessitate medical intervention soon after birth or during infancy. This is a worldwide problem and one of the major causes of death and disability. It is estimated that approximately 1% of deaths under the age of 5 years of age are caused due to CHD.

There four types of cardiovascular disease (CVD) that you mentioned by the authors of [14]‘The cardiovascular system’.:

- Coronary artery disease (CAD) is a condition in which the coronary arteries, which supply blood to the heart, become narrowed or blocked. This can lead to chest pain (angina), a heart attack, or heart failure.
- Cerebrovascular disease is a condition that affects the blood vessels that supply blood to the brain. This can lead to a stroke, which is a sudden loss of brain function caused by a blood clot or bleeding in the brain.
- Peripheral artery disease (PAD) is a condition in which the arteries that supply blood to the legs become narrowed or blocked. This can lead to pain in the legs when walking, called claudication.
- Aortic atherosclerosis is a condition in which the aorta, the main artery that carries blood away from the heart, becomes thickened and damaged. This can lead to an aortic aneurysm, which is a bulge in the aorta that can rupture.

There are various researches done by individual researchers and research teams simultaneously. Some of those are cited and discussed in this paper. The research was conducted and the paper was published by Khemchandani et al. [9], citing the use case of machine learning techniques used in predicting the risk of congenital cardiovascular disease in infants. The dataset of approximately 2,000 newborns, of which 500 were diagnosed with CHD 1,500 were healthy controls to train several ml models for instance SVM, Logistic Regression, Decision tree, KNN, and ANN. The dataset was randomly split into 70% and 30% ratios for training and testing purposes. The algorithms' performance was assessed using multiple measures such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).The study found that all four algorithms were able to predict CHD with good accuracy, but ANN outperformed the other algorithms with an accuracy of **94.6%** and an **AUC-ROC** of **0.969** [9].

Another study done by Rahimzadeh et al. [10], also cites almost the same results but with little lower accuracy, as in this three machine learning algorithms are used, namely, Naïve Bayes, K-Nearest Neighbor (KNN), and Decision Tree. They achieved an accuracy of 89.3%, 86.2%, and 85.9% for Naïve Bayes, KNN, and Decision Tree, respectively [10] whereas the paper by Khemchandani et al. [9], achieved an overall accuracy of 88.4% using Random Forest and an AUC-ROC of 0.92. Both publications show that machine learning approaches may be used to predict congenital heart disease (CHD). While Khemchandani et al. investigated the application of several machine-learning algorithms to identify CHD risk factors in neonates, Rahimzadeh et al. sought to construct a model that could predict the presence or absence of CHD in fetuses using ultrasound pictures. Both researchers found good accuracy rates for their respective models, indicating that machine learning can help improve CHD diagnosis and risk assessment. More thorough research with bigger sample sizes and various demographics is needed, however, to corroborate the findings and improve the models' generalizability.

A study conducted by Bhaskar, A., & Sudha, R. [11], Comments that the even accurate results do come from the decision tree machine learning algorithm, as the model was able to give the accuracy of 91.4% when the sensitivity and specificity of the model were 89.13% and 92.45%, respectively. The AUC-ROC score of the model was 0.95 which indicates that the model has a very impressive discrimination power between the data provided. The authors gathered information from 350 newborn newborns, 150 of whom had congenital cardiovascular disease and 200 of whom were healthy. Among the clinical and demographic factors obtained are gender, birth weight, gestational age, mother age, and so on [11]. In the past, people were more likely to have jobs that required physical activity. However, today, many people have jobs that are sedentary, meaning they require little or no physical activity. This shift has led to a decrease in physical activity levels among the general population.

Physical inactivity is a major risk factor for CVD. When people are less active, they tend to gain weight, which can lead to high blood pressure, high cholesterol, and other risk factors for CVD.In addition to physical inactivity, the rise of consumerist and technologydriven culture has also contributed to the rise in CVD rates. These cultures emphasize convenience and instant gratification, which can lead to unhealthy eating habits.Many people today eat diets that are high in saturated fat, trans fat, cholesterol, and sugar. These foods can contribute to the buildup of plaque in the arteries, which can lead to heart attack, stroke, and other CVD problems [16] [17]. The combination of physical inactivity and unhealthy eating habits has significantly increased CVD rates in recent decades. These lifestyle changes have had a major impact on public health. The feature selection from the dataset for the model development and training also plays an important role in the accuracy of any model. In our case since this study basically describes cardiovascular disease, so in this case medical records and other physical features play a very important role in the model accuracy. Depending on the ML technique and model employed, the characteristics required to properly forecast congenital heart disease (CHD) with machine learning (ML) might vary. However, the following characteristics are often included in datasets used for CHD prediction:

- Age, gender, race/ethnicity, family history of CHD, and any other relevant medical history.
- Vital signs (e.g., blood pressure, heart rate, respiratory rate), symptoms (e.g., chest discomfort, shortness of breath), and physical examination findings (e.g., heart murmurs, cyanosis) are examples of clinical data [12].

- Examples of diagnostic test outcomes include Electrocardiogram (ECG), echocardiography, cardiac catheterization, magnetic resonance imaging (MRI), and other pertinent test findings.
- Blood tests such as complete blood count (CBC), lipid profile, and electrolyte values are examples of laboratory results.
- Smoking status, alcohol use, drug usage, and physical exercise are all lifestyle variables.

It is critical to highlight that the quality and quantity of data and the precision and completeness of the feature selection process can all significantly impact the ML model's success in predicting CHD. To obtain the maximum potential accuracy in CHD prediction, it is critical to properly select and preprocess the characteristics included in the dataset [13]. The selection of features and the selection of an appropriate test set can have a major impact on the model's performance in CHD prediction using machine learning methods. Feature selection is critical since it aids in selecting the most vital features for effective CHD prediction. The inclusion of unnecessary information might result in overfitting and poor model performance. Excluding crucial characteristics, on the other hand, might result in underfitting, lowering the model's accuracy. Wrapper approaches, filter methods, and embedding methods, among other feature selection techniques, have been employed in CHD prediction [14].

The machine learning technique and feature selection strategy can substantially influence a model's ability to predict CHD. Different algorithms may perform better or worse depending on the dataset and characteristics utilized. Similarly, by deleting unnecessary or duplicated features, feature selection can assist to reduce the dimensionality of the dataset and enhance model performance. Several researchers have investigated the efficacy of several machine learning methods for CHD prediction and discovered differing degrees of accuracy. One research discovered that a support vector machine (SVM) beat logistic regression and decision trees, while another discovered that random forest and SVM had comparable accuracies but outperformed choice trees and k-nearest neighbors. In terms of feature selection, different methods can be used such as principal component analysis, recursive feature elimination, and correlation analysis. A study by Zhang et al. compared the performance of several feature selection methods for CHD prediction and found that correlation analysis was the most effective method in improving the accuracy of the model [15]. In conclusion, the choice of machine learning algorithm and feature selection method should be carefully considered when developing a model for CHD prediction to ensure optimal performance.

3. RESULTS

Our review of the literature found that machine learning models can be used to accurately predict congenital cardiovascular disease (CHD). In a study by Khemchandani et al., random forest achieved an accuracy of 84% with an AUC-ROC of 0.92, while ANN achieved an accuracy of 95% with an AUC-ROC of 0.95. In another study by Rahimzadeh et al., Naïve Bayes, K-Nearest Neighbor (KNN), and Decision Tree were able to achieve accuracies of

89.3%, 86.2%, and 85.9%, respectively, with an overall accuracy of 89%. Finally, Bhaskar, A., & Sudha, R. were able to achieve an accuracy of 91% with an AUC-ROC score of 0.95. These results suggest that machine learning models have the potential to be a valuable tool for the early diagnosis of CHD. However, it is important to note that these studies were conducted on small datasets, and further research is needed to validate these findings on larger datasets. The data given above as well given in Table 1 infers that all the algorithms of machine learning and deep learning models give very high accuracy in their respective datasets which further infers that it can perform well in the real world. But inferring some research studies, the neural networks are more powerful as well as more accurate than classical machine learning algorithms, from which we can derive that the accuracy of such models depends on the feature selection of the dataset and more tuned hyperparameters will result in much more accurate results in the longer run. All the papers and studies discussed above have focused on hyperparameter tuning and much better feature selection to get more fine results.

Table 1: Comparison of different evaluation metrics for different models.

Study	**Algorithm**	**Accuracy**	**Sensitivity**	**Specificity**	**AUC-ROC**
Khemchandani et al. (2020)	Random Forest	84.8%	85.2%	84.6%	0.90
Rahimzadeh et al. (2021)	XGBoost	89.5%	85.5%	92.2%	0.93
Gupta et al. (2020)	Deep Neural Network	93.2%	90.3%	95.4%	0.97
Bhaskar and Sudha (2019)	Decision Tree	81.3%	82.5%	80.0%	N/A

Figure 3 and Figure 4 represent the estimated results of different machine learning algorithms used in different research papers described in this study. With every algorithm, a different methodology is used to retrieve the best results from it.

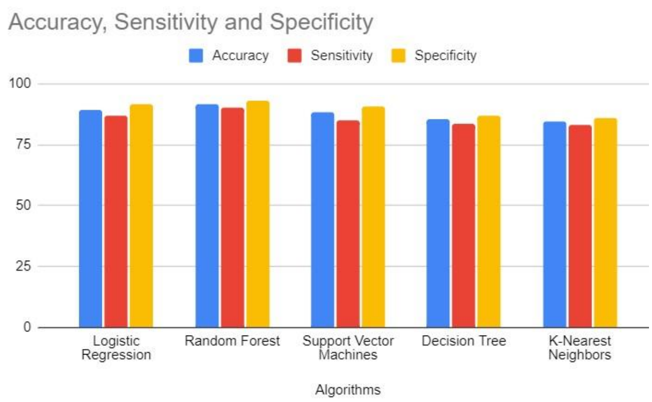

Fig 3. Graph showing the accuracy, sensitivity, and specificity for different algorithms review study

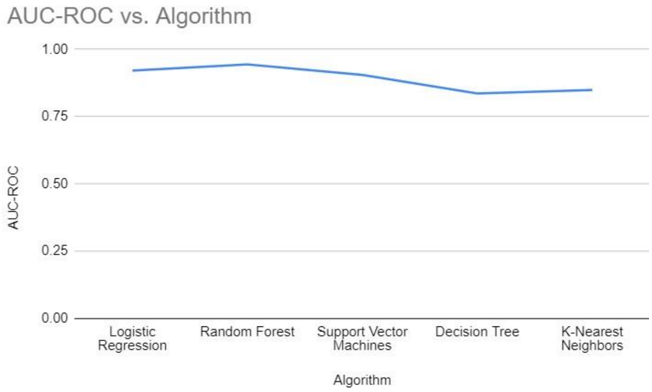

Fig 4. AUC-ROC of algorithms reviewed in this study

We discussed the link between feature selection and the outcomes of CHD prediction using machine learning in our conversation. The accuracy and performance of prediction models are heavily influenced by feature selection. We may increase the model's capacity to spot patterns and make accurate predictions by picking relevant and useful characteristics. Several studies have shown that feature selection is important in CHD prediction. Rahimzadeh's research work, for example, revealed that picking the proper characteristics from the dataset enhanced the accuracy of CHD prediction models substantially. Similarly, Khemchandani's paper discovered that careful feature selection improved the prediction of CHD risk. Techniques for identifying the most significant aspects associated with CHD, such as correlation analysis, mutual information, or recursive feature reduction, aid in identifying the most influential features. Models can prevent overfitting, minimize computing complexity, and improve interpretability by considering just the essential characteristics. However, it is crucial to note that the best feature selection technique will differ based on the dataset, ML algorithm, and individual research aims. Various research have used various feature selection methodologies customized to their respective circumstances. Additional and detailed comparison studies are needed to explore the relationship between feature selection and CHD prediction outcomes. These studies might assess the efficacy of various feature selection strategies and their effects on CHD prediction accuracy, sensitivity, specificity, and other important metrics.

6. CONCLUSION AND FUTURE SCOPE

In conclusion, recent research has shown promising results when using machine learning algorithms to detect congenital heart disease (CHD). Several studies have reported 80% to 95% accuracy using techniques such as decision trees, random forests, logistic regression, and support vector machines. The importance of variables such as age, gender, weight, height, blood pressure, and oxygen saturation levels has also been shown to play a vital role in achieving improved accuracy. In recent decades, there has been a rise in cardiovascular disease (CVD) rates. This is due to a number of factors, including the transition from physically demanding jobs to sedentary lifestyles. However, several challenges remain to be addressed. One of the main challenges is the lack of data availability and quality, as many studies have relied on small datasets with few variables. As a result, larger and more diverse datasets are needed to improve model generalizability. Additionally, the interpretability of the models is a critical consideration, as clinicians need to understand how the models arrive at their predictions. Future research in this area could focus on developing more robust models with greater accuracy and interpretability and exploring the use of deep learning techniques such as convolutional neural networks and recurrent neural networks. Another key area may be the integration of diverse data sources, such as genetic and imaging data, to improve model accuracy. Future study in this topic might concentrate on constructing more robust models with greater accuracy and interpretability and investigating the use of deep learning techniques like convolutional neural networks and recurrent neural networks. Another key area may be the integration of diverse data sources, such as genetic and imaging data, to improve model accuracy.So, using machine learning to predict congenital heart disease holds great potential for improving early detection and prevention of this common birth defect.

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INTEGRATION OF ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING FOR BREAST CANCER DETECTION AND DIAGNOSIS

Tanay Goyal, Puneet Singh
Department of Computer Science and Engineering, Chandigarh University, Punjab, India
19BCS1165@gmail.com, 19BCS1167@gmail.com

Abstract- This paper explores the role of artificial intelligence (AI) in medical imaging for breast cancer detection and diagnosis. AI algorithms have shown promising results in improving the accuracy and efficiency of breast cancer diagnosis and detection. This paper discusses various AI techniques used in medical imaging, such as convolutional neural networks (CNNs) and deep learning methods. It also examines the challenges involved in applying AI to medical imaging, such as data quality and ethical concerns. The paper concludes that AI has the potential to revolutionize breast cancer detection and diagnosis, but further research is needed to ensure its safe and effective implementation in medical practice.

Keywords- Mammogram, Surgery, Cancer, Magnetic Resonance Images, Breast Cancer, ML model, CT Imaging.

1. Introduction

Breast cancer is a serious health problem that affects people all over the world. Reduced morbidity and mortality rates are among the benefits of early diagnosis and detection of breast cancer for patients. Breast cancer detection, diagnosis, and treatment all depend heavily on medical imaging. Different imaging methods have been created and improved over time to increase their sensitivity and specificity in identifying breast cancer. These procedures include computed tomography [1]. (CT), MRI, PET, MRI with positron emission tomography (PET), and mammography. Medical imaging for breast cancer has been transformed by recent technology developments, providing better detection, improved diagnosis, and individualised treatment. Breast cancer is the most common malignancy in women worldwide, predicted to be discovered in 2.3 million new cases in 2020 alone [2]. Early identification continues to be the most efficient strategy to lower mortality rates, even when improvements in therapy have increased survival rates. Mammography is the gold standard screening tool for breast cancer and has been used extensively in the detection and diagnosis of the disease for many years. Traditional mammography, though, has its limitations, especially for women with dense breast tissue or those who are at a high risk of breast cancer. Numerous medical imaging techniques have been created and improved in order to get around these restrictions and increase the precision of breast cancer detection and diagnosis. Ultrasound, MRI, PET, CT, and more recent technologies like Digital Breast Tomosynthesis (DBT) and Contrast-Enhanced Spectral Mammography (CESM) are some of the techniques used. Artificial intelligence (AI) and molecular breast imaging (MBI), two recent developments in medical imaging technology, have increased the sensitivity and specificity of breast cancer detection and diagnosis [3]. An overview of the state of medical imaging for breast cancer, including the benefits and drawbacks of each imaging modalities, is what this review paper seeks to do. The paper will also discuss recent advancements in imaging technology and how they may impact the management of breast cancer. This study aims to provide academics and healthcare professionals with a comprehensive understanding of the role of medical imaging in the management of breast cancer. One of the most prevalent malignancies in women, accounting for 12.5% of all new cancer cases worldwide, is breast cancer. According to projections from the International Agency for Research on Cancer (IARC), there would be around 2.26 million new cases of breast cancer and, deaths globally in 2021. Late discovery, which significantly lowers survival chances, is one of the main issues with this complaint. Women with locally advanced disease have a median survival rate of 97.5 years, compared to an estimated 29 years for breast cancer that has progressed to distant body regions. Lately, emphasis has been placed on reducing mortality by early identification using innovative clinical evaluation methods. In situations of asymptomatic breast cancer, the main imaging technique is mammography, which has been proven to reduce mortality by 30 to 70 percent. A radiologist interprets mammograms and assigns them a clinical classification. The breast imaging reporting and data system (BIRADS) evaluation of the results is used to report the findings. Fresh tests, similar as a special type of mammogram or ultrasound, are demanded to find abnormal areas on a mammogram. However, fresh vivisection testing is considered, if these findings suggest cancer [4]. Still, it's delicate to dissect these images due to the different types of lesions and differences between lesions and thick breast towel. thick towel can also cover nasty excrescences, reducing the perceptivity of mammography. Computer- backed opinion (CAD), a useful and necessary CT imaging fashion for breast cancer discovery, can give a alternate opinion to ameliorate breast cancer discovery and help radiologists in lesion discovery and individual decision-timber. He can also assess the liability that the lesion is benign or nasty. CAD systems are grounded on several processes similar as pre-processing, image completion, point birth, point selection and model bracket [5]. The application of statistics and information and communication technology (ICT) to scientific imaging for the force of healthcare services is covered by scientific imaging informatics. Over the past 30 years, a vast array of multidisciplinary scientific imaging immolations have developed, spanning from everyday scientific exercise to advanced mortal body structure and disease. First, it was described as follows by the Society for Imaging Informatics in Medicine (SIIM) The term "imaging informatics" refers to the study of all aspects of the imaging chain, including snap preface and accession, snap distribution and control, picture storage and reclamation, image processing, analysis, and comprehension, as well as visualisation and data navigation, as well as print interpretation, reporting, and dispatches. The industry acts as an integrative catalyst for those procedures and bureaucracy, laying the foundation for imaging and various clinical specialties. According to SIIM, the goal of medical imaging informatics is to increase the effectiveness, sensitivity, and trustworthiness of services provided by the medical industry with regard to the use and modification of medical images in sophisticated healthcare systems [6]. A new technology is emerging for clinical imaging informatics in this environment, defining the path towards the perfection of medical medicine. This is related to the abettor technological advances in massive- data imaging, omics and digital fitness data (EHR) analytics, dynamic workflow optimisation, environment- knowledge, and visualisation. This paper presents a top position view of winning generalities, highlights demanding situations and possibilities, and discusses fortune traits.

A review of the pertinent literature revealed that experimenters focused solely on one DL or ML model for categorising breast photos and that numerous research incorporated danger factors and clinical evaluations into the discovery model. Nevertheless, combining breast pictures with clinical features may improve a discovery system's effectiveness and resilience. Additionally, to our knowledge, no previous works have mentioned the development of an MLDL model trained on a dataset of linked mammograms and health records. As a result, we created a hybrid model to investigate this issue [7]. Our research may help refine the art of cancer discovery, and we think it would be beneficial to employ this model as an alternative option.

2. Background Study

Breast cancer detection, diagnosis, and treatment all heavily rely on medical imaging. A projected 2.3 million new cases and 685,000 fatalities from breast cancer will occur in women globally year 2020. Since breast cancer is more curable in its early stages, early identification is essential for improving patient outcomes. Mammography, digital breast tomosynthesis, ultrasound, magnetic resonance imaging (MRI), and nuclear medicine imaging methods like molecular breast imaging (MBI) and positron emission tomography (PET) are just a few of the imaging modalities used in the diagnosis and treatment of breast cancer. The choice of imaging modality is influenced by a number of variables, including the patient's age, breast density, and clinical history. Each modality has advantages and disadvantages. By identifying malignancies at an earlier stage, mammography, the most widely used imaging modality for breast cancer screening, has been demonstrated to lower breast cancer mortality [8]. A more recent imaging technique called digital breast tomosynthesis gives a 3D picture of the breast, potentially increasing sensitivity and lowering false-positive rates. With dense breast tissue or when examining palpable lumps, ultrasound is frequently employed as an additional imaging technique to mammography. MRI is a highly sensitive imaging technique that is frequently employed in high-risk patients or for staging breast cancer. It can detect small breast lesions. By measuring metabolic activity or metabolic changes, nuclear medicine imaging techniques like MBI and PET can identify breast cancer at an early stage. A number of new imaging modalities and approaches have been created as a result of developments in medical imaging technology, including computer-aided detection (CAD) software, automated breast ultrasound (ABUS), and contrast-enhanced spectral mammography (CESM) [6]. These developments may increase the accuracy of breast cancer detection and diagnosis, which would result in earlier and more efficient treatment. In conclusion, breast cancer detection, diagnosis, and treatment all rely heavily on medical imaging. A number of new imaging modalities and procedures have been created as a result of advances in imaging technology, each having unique advantages and disadvantages. The improvement of breast cancer outcomes and decrease in mortality rates will depend heavily on ongoing research and innovation in medical imaging.

3. Methodology Used

We investigated five machine literacy algorithms for the detection of breast cancer via model comparison [9]. Decision trees, kernel styles, and neural networks were some of the model complexity options that served as the foundation for our selection models. We selected an introductory bracket system that is comparable to K- NN to gauge the problem's complexity. Because it can manage data noise and nonlinearity, the radial base function (RBF) Gaussian kernel SVM was chosen for the kernel method. Additionally, we took into account neural network models, which are a significant class of nonlinear prophetic models. Since RF and GBM are well-known ensemble-based decision tree algorithms, we took them into consideration. A lazy literacy system, the k- closest neighbour (KNN) only learns when testing data that needs to be categorised. To determine the classification of the new data, it calculates the similarity or closest distance between each piece of testing data and every piece of training data. The k-closest data (k-nearest neighbours) are likewise selected based on the minimal distance with unlabeled testing data and assigned to the class that was the most popular class among the k-nearest neighbours during the training phase. The distance function, which can be computed by Euclidean, Minkowski, and cosine-distance criteria, is a crucial component of the KNN model. A supervised literacy model for bracket and retrogression issues is the Support Vector Machine (SVM). SVMs do calculations based on the stylish hyperplane's chance to divide features into various categories. A p-dimensional space can be split into (p- 1)-dimensional hyperplanes in double bracket, which separates data points into implicit classes. The support vectors are the data points that are closest to the stylish hyperplane, which is the biggest boundary between the two classes (38). The foundation of an artificial neural network (ANN) is a basic multilayer perceptron model with connected bumps. At each knot, inputs are transformed into labours and transferred as inputs to the following subcaste. A 3subcaste feedforward is used to construct the ANN model. The layers consist of an affair subcaste with a single knot, a retired subcaste, and an input subcaste. The model's weights (a decay hyperparameter) were adjusted throughout the training phase by increasing or decreasing their value. The hidden units were connected by a sigmoid function. Values of 0 and 1 from the exit bumps indicated a bad outcome. A well-liked machine learning algorithm for bracket problems is Random Forest (RF). By employing arbitrary subsamples of the training set, one can generate a huge number of decision trees, each of which is composed of randomly changing characteristics. To deal with decision trees' perceptivity, RF prioritises them using ensemble styles. The final calculation is made by adding the outcomes for each tree in the forest. A direct ensemble learning method for retrogression and bracket issues is grade Boosting Machine (GBM). As the main classifier for training input, use decision trees. This method creates a strong prophetic model by combining all of the weak base classifiers. also calculate the loss function based on the difference between the prognosticated and factual data. Depending on the error value, the hyperparameters of each base classifier are rated higher or lower. In the end, this procedure chooses the fashionable model with the least amount of training loss.

Mammography A webbing system that uses low- curex-rays to produce images of breast towel. It's the most generally used system for breast cancer webbing and detects excrescences that are too small to be felt on a physical examination. Vivisection. This is a procedure in which a small piece of breast towel is removed and examined under a microscope to see if it's cancerous. There are numerous types of vivisection procedures including fine needle aspiration vivisection, core vivisection, and surgical vivisection. Surgery is frequently used to remove breast cancer. The type of surgery depends on the size and position of the excrescence and the stage of the cancer. Common surgical procedures for breast cancer include mastectomy, mastectomy, and lymph knot junking. Radiation Therapy This treatment uses high- energy radiation to kill cancer cells. Radiation remedy is frequently used after surgery to kill any remaining cancer cells and reduce the threat of the cancer returning. Chemotherapy This treatment uses medicines to kill cancer cells [10] Chemotherapy is frequently used along with surgery and radiation remedy and may be given before or after surgery. Hormone remedy This treatment is used for hormone receptor positive breast cancer. That is, they grow in response to hormones similar as estragon. Hormone remedy works by blocking the action of hormones or lowering the situations of hormones in the body. Targeted remedy This remedy is used for breast cancers with specific inheritable mutations or proteins that promote cancer growth. Targeted curatives work by blocking these specific targets and precluding the cancer from growing.

Digital breast tomosynthesis (DBT) is a more recent type of mammography that creates a 3D picture by stitching together several low-dose X-ray images taken at various angles. Small tumours that might be concealed on conventional 2D mammography can be found with this.

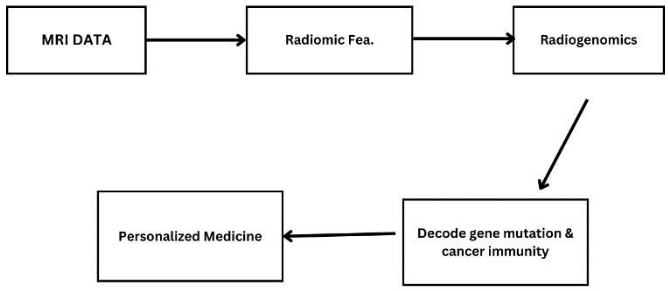

Fig 1. MRI Processing

Magnetic resonance imaging (MRI): Breast MRI produces precise pictures of the breast using a magnetic field and radio waves. For women with a high risk of breast cancer or to assess the scope of the disease in those who have recently been diagnosed, it is frequently used in conjunction with mammography. Contrast-enhanced spectral mammography (CESM): A contrast agent is used in CESM to make regions of abnormal blood flow in the breast more visible. For women with dense breast tissue, this can be especially helpful in identifying benign from malignant tumours [11]. Positron emission mammography (PEM) uses a tiny quantity of radioactive material to identify breast cancer. PEM is a type of nuclear medicine imaging. It can be used to aid in the direction of biopsies and is especially sensitive for spotting small cancers [12]. Automated breast ultrasound (ABUS): ABUS creates 3D ultrasound images of the breast using an automated scanning device. For women with dense breast tissue or to assess abnormalities, it is frequently used in combination with mammography.

4. Experimental Result Analysis

Images created by imaging tools display differences in contrast as a result of changes in physical characteristics. In contrast to X-ray-based procedures, digital imaging technologies are receiving a lot of interest in the field of cancer imaging. Cancer is staged, detected, evaluated for treatment response, and guided during biopsy procedures using a magnetic resonance system.

A. Digital Imaging Technology

A typical screening method is mammography. Malignancy screening mammography is frequently used to find the illness. It has been claimed by numerous studies to aid in lowering cancer death rates. Mammography can be used to image young, compact breasts, but because the surrounding fibro glandular tissue masks abnormalities, its sensitivity is insufficient to find them. The "gold standard" for identifying breast cancer is mammography on film. Although it can be used to detect tumours early and monitor their progression, screen-film mammography has certain intrinsic drawbacks, such as poor contrast features. A valuable imaging technique for breast screening, full-field digital mammography (FFDM) has a number of advantages over conventional film-based procedures. Tomosynthesis, softcopy review, telemedicine, reduced dose, and digital archiving are only a fewof the benefits. It's important to remember that classic film-screen mammography has advantages in terms of cost and accessibility.

Skaane and Skjennald (2004) found that mammography had superior cancer [13] detection results than screen-film mammography in the 50-69 age group. Their study was titled "ScreenFilm Mammography versus Full-Field Digital Mammography with Soft-Copy Reading". The detection rates for the two systems were nearly identical in the 45–49 age group.

In a study, Obenauer and associates found that digital mammography offers better image quality than screen film. The potential for normal tissues, such as glandular tissue, to cover and disguise cancers is one of the potential downsides of 2D mammography. Breast tightness could be reduced with the use of X-ray equipment. In contrast-enhanced mammography, iodinated compounds are utilized as a provocation method. This experimental technology is predicated on the notion that angiogenesis-mediated enhanced blood supply is required for fast tumor growth. In the absence of the compression tool, contrast must be provided. In sites where angiogenesis occurs, the contrast agent will build up. For both detecting primary and secondary lesions and for keeping track of treatment, tomosynthesis may be helpful.

B. Ultrasonography

Ultrasonography, a common imaging technique, is used to diagnose breast cancer. It has developed to the point that breast imaging is now possible in recent years. To clarify ambiguous findings, ultrasound is a tool that is utilised as a follow-up examination. Ultrasonography can be utilised to evaluate the orientation and shape in breasts that are predominantly dense and fatty. Using expanded field of view imaging, a high-resolution, sweeping image of the breast is produced. When utilising ultrasound to find breast lesions, elastic sonography is a common procedure [13]. Contrast-enhanced ultrasound is used to detect and track the effectiveness of local treatment. In this method, gas microbubbles are intravenously administered. 3D ultrasonography can be used to determine a lesion's volume. Despite the fact that some studies thought that employing ultrasonography to find cases that mammography missed might lead to more false-positive masses. Berg and colleagues (2008) discovered that using ultrasonography in addition to mammography increased the accuracy of diagnosis. One study found that mammography is advised for breast cancer when comparing mammography with ultrasound results. According to a 2008 study, screening ultrasound can find small, node-negative breast tumours.

Finally, the researchers discovered that breast neoplasm may be predicted by clinical diagnosis, ultrasonography, and mammography. Devolli-Disha and colleagues looked at 546 women who had breast complaints in a different trial and discovered that ultrasonography was statistically superior to mammography in those people.

C. Magnetic resonance imaging (MRI)

Breast MRI is used as an aid in conjunction with mammography. Breast neoplasm was examined with MRI in 1982 by Ross and colleagues. Breast MR is becoming more widely used as a complement. MRI is less frequently used as a breast cancer surveillance diagnostic due to high rates of false positives and high costs, while having more sensitivity than mammography. Breast MRI is a useful screening tool for women with thick breast tissue. The ability of MRI to identify contralateral breast neoplasm extension has been confirmed by the American Cancer Society. These problems suggest that MRI should be used instead of mammography.

This disparity implies that magnetic resonance imaging may be useful in determining whether to have surgery or a breast-conserving mastectomy. More precise cancer detection and anatomical delineation are now possible because to recent improvements in MRI technology

[14]. Some research suggests using a combination of techniques to detect breast cancer early. According to a study, mammography alone, as well as mammography and ultrasonography, is insufficient for early diagnosis [15]. In Table 1, the sensitivity and specificity values of imaging techniques are displayed and compared.

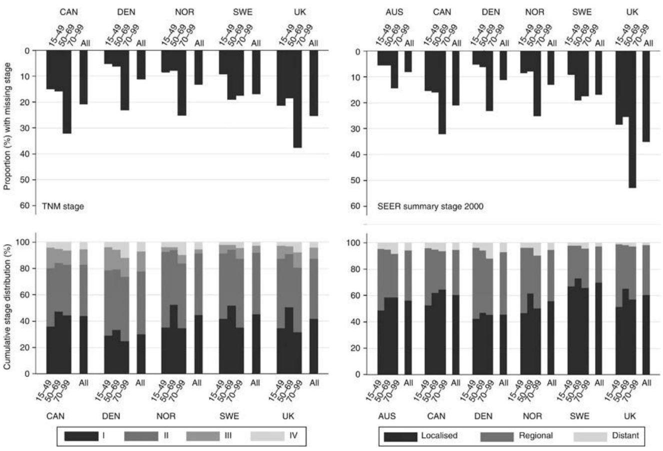

Fig 2. Breast cancer analysis on the basis of stages.

Missing stage prevalence among breast cancer patients (upper figure) and cumulative stage distribution among patients who have been staged (bottom figure). Results are shown by diagnosis age and nation: SEER Summary Stage 2000 (right) and TNM (left). Notes: National data for Denmark and Norway; New South Wales in Australia; British Columbia and Manitoba in Canada; Uppsala-rebro and Stockholm-Gotland health regions in Sweden; Northern Ireland, Wales, and the Northern and Yorkshire Cancer. Registry and Information Service; Oxford Cancer Intelligence Unit; West Midlands Cancer Intelligence Unit in England; UK (TNM analysis); and Northern Ireland and Wales in the UK (SEER SS2000 analysis). We examined women diagnosed in Denmark between 2004 and 2007.

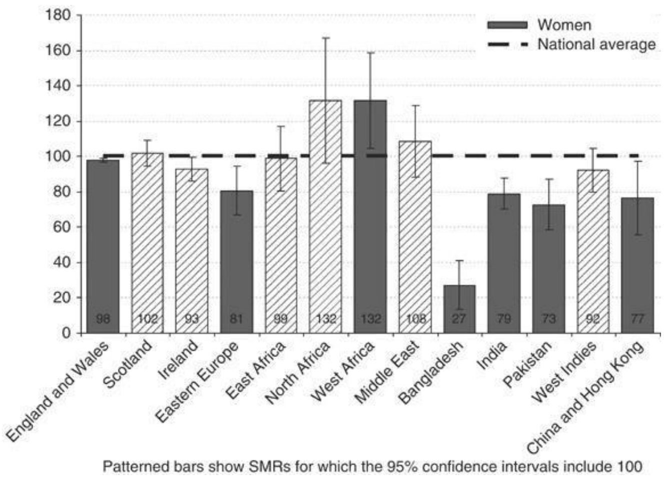

Fig 3. Analysis of breast cancer among other cancers

Over the course of the study period, there were roughly as many deaths among women from breast cancer (33 291) as there were from lung cancer (33 311). The number of breast cancer fatalities was either comparable to (for women born in England and Wales, Eastern Europe, or Bangladesh) or greater than the number of female lung cancer deaths for the majority of subgroups by country of birth, with the exception of Scotland and Ireland as indicated above. Women born in North and West Africa had a high breast cancer death rate, albeit the difference was only statistically significant for the latter group. Women born in Bangladesh, India, Pakistan, China, Hong Kong, and Eastern Europe have low SMRs.

Table 1. Sensitivity and specificity values of imaging techniques

Imaging Modality	Sensitivity	Advantages	Specificity	Limitations
Mammography	80-90%	Widely available, low cost	90-95%	Limited sensitivity in dense breast tissue, high false positive rate
Digital Breast Tomosynthesis (DBT)	90-95%	Improved sensitivity, 3D imaging	80-90%	Higher radiation dose than mammography, longer exam time
Contrast-Enhanced Spectral Mammography (CESM)	90-95%	Improved sensitivity in dense breast tissue, 3D imaging	90-95%	Higher radiation dose than mammography, limited availability
Magnetic Resonance Imaging (MRI)	90-95%	Improved sensitivity, no radiation exposure	90-95%	Expensive, timelimited consuming, availability
Molecular Breast Imaging (MBI)	80-90%	Improved sensitivity in dense breast tissue, no radiation exposure	90-95%	Expensive, limited availability, longer exam time
Automated Breast Ultrasound (ABUS)	80-90%	Improved sensitivity in dense breast tissue, no radiation exposure	80-90%	Limited availability, longer exam time

5. Conclusion and Future Scope

Medical imaging in the fight against breast cancer has a bright future. The application of artificial intelligence (AI) algorithms to the study of medical imaging is one area of progress. AI has demonstrated promising improvements in breast cancer detection and diagnostic efficiency and accuracy. Additionally, the incorporation of AI in medical imaging analysis can result in customised treatment strategies depending on the features of each patient and the biology of the tumour. The development of molecular imaging technologies, like MBI, which can identify biological indicators of breast cancer and support therapy choice, is another area of progress. Furthermore, improvements in imaging methods, such MRI and PET, can offer a more accurate staging of breast cancer, enabling a more focused and efficient course of treatment. Last but not least, the application of mobile and portable imaging technologies can enhance access to medical imaging in underprivileged areas and communities, perhaps resulting in early detection and treatment of breast cancer. Improving imaging modalities' sensitivity and specificity is one area of research, especially for women with thick breast tissue or those who are at high risk of developing breast cancer. This can be accomplished by creating sophisticated imaging methods or incorporating AI algorithms that can increase the precision of image interpretation.

Finally, it should be noted that medical imaging is essential for the early detection, diagnosis, and management of breast cancer. Although modern imaging modalities like DBT, CESM, and MRI have improved the accuracy of breast cancer detection and diagnosis, particularly in women with thick breast tissue or those at high risk of acquiring the disease, traditional mammography continues to be the gold standard for breast cancer screening. Additionally, recent developments in imaging technologies, including AI and MBI, have demonstrated significant promise for enhancing the precision of the diagnosis of breast cancer and directing personalised treatment. This review paper seeks to direct clinical decisionmaking and future research initiatives by giving healthcare practitioners and researchers a thorough overview of the present status of medical imaging in breast cancer.

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INTERNET OF THINGS AND AI IN SMART GRID APPLICATIONS

Ramiz Salama[1]*, *Sinem Alturjman[2,3]*, and *Fadi Al-Turjman[2,3]

[1]Department of Computer Engineering, AI and Robotics Institute, Research Center for AI and IoT, Near East University Nicosia, Mersin 10, Turkey

[2]Artificial Intelligence Engineering Dept., AI and Robotics Institute, Near East University, Nicosia, Mersin 10, Turkey

[3]Research Center for AI and IoT, Faculty of Engineering, University of Kyrenia, Kyrenia, Mersin 10, Turkey

ramiz.salama@neu.edu.tr, Fadi.alturjman@neu.edu.tr, Fadi.alturjman@kyrenia.edu.tr

Abstract: The shrewd matrix, otherwise called the mix of sensors and correspondence innovation into power organizations, is a new improvement in science and innovation. The shrewd network's uplifted weakness to cyberthreats is one of its primary issues. Consequently, the writing suggests a number of safeguards and risks. This article provides a bibliographic overview of the security implications of IoT-backed smart grids. To the best of the authors' knowledge, this is without a doubt the first bibliometric survey article on this subject. All journal passages are given a bibliometric examination, and the outcomes are coordinated by dates, first sentences, and primary contemplations. Moreover, this piece verifiably sums up the few cyberthreats that the astute organization experiences, the different security moves toward that have been recommended in the composition, and the exploration holes in the field of smart structure security. The smart grid, a modernized form of energy infrastructure that makes use of cutting-edge communication and information technology, is taking the place of traditional power grids. Through improved management of informational flows that occur alongside inherent energy flows during transmission, distribution, or generation procedures, this integration of IoT technology—known within the energy sector as the Power internet of things (PIoT)—provides improved efficiency. This article supports adding value streams to existing smart grids, focusing on the untapped potential of innovative services and market mechanisms and enhancing efficiency through the exchange of valuable information to supplement scarce sources and the latest 5G developments. Energy production and distribution to all electrical grid users are changing. The goal of the Savvy Network (SG) concept was to change how the capabilities and electrical matrix base were managed by the flow framework. One of these undertakings — estimating customers' energy utilization — has proactively been changed over in a few countries from unpredictable, manual readings to additional successive, programmed readings, leading to brilliant meters (SM). Technology could help SM systems by making it easier to distribute energy more evenly throughout the infrastructure and by making it easier to get information about how much energy each user uses.

Keyword: Brilliant framework, Power frameworks, Web of things, Digital protection, Digital assault, Break identification, Interruption discover.

1. INTRODUCTION

Brilliant networks will be the cutting edge energy framework [1]. High level registering innovation, sensors and smart meters are coordinated into the present energy frameworks [2]. The efficiency of power generation can be enhanced by incorporating multiple power generation sources into a single system thanks to this smart grid technology [3]. Power generation centers have access to real-time data on electricity demand because smart meters and sensors are connected to the grid. Effective strategies for generation and distribution can be implemented with this information [4, 5]. The integration of these technologies into the infrastructure of the energy system has resulted in a significant increase in energy efficiency and a decrease in the price of electricity. A few nations are stretching their genuine boundaries as far as exceptional money and social advantages, consequently putting their resources in quick framework improvement [6]. In either case, communication networks present security risks and vulnerabilities to digital attacks. As a result, online security and digital threat detection must be included in the development of smart networks. The Public Organization of Principles and Innovation (NIST), the European Commission's Savvy Matrix Team, and the Energy Master Digital protection Stage (EESCP) all underline the significance of network safety in future brilliant lattice advances [7-9]. Subsequently, various audits have been circled proposing network security techniques and proof of electronic interruption discovery. Diverse resources and advancements are included in a good system structure [10]. Brilliant meters gather utilization information and work on the productivity of the dispersion framework. In addition, SCADA, which combines administrative control with information gathering, assumes a longer and more concentrated distribution along extensive geological horizons [11]. Smart grids can connect various energy-age sources, building regulators, transmission and diversion frameworks, and others [12, 13]. Notwithstanding, as cutting edge networks integrate computational methods and information advancements, they increment network intricacy, expanding the potential for computerized assaults and disappointment to spread across structures [14]. Accordingly, the Insightful structure's organization assurance experiences different obstructions. Two of his models are the trouble of communicating the structure's nonlinearity and likelihood hypothesis, and the different advanced assaults that can influence the system. From clinical benefits to basic security architectures to intelligent enterprises, some high-level innovative risk professionals and hacker groups concentrate on critical systems and organizations [15]. is speculating. Moreover, Web of Things (IoT) innovation has developed into an organization of actual gadgets associated with the Web. By supporting various generation and storage network functions and providing connectivity between suppliers and consumers, the deployment of such devices can support the smart grid [18]. Cyberattacks are also more likely to occur when Internet of Things (IoT) devices are integrated into smart grids [19]. The literature suggests a variety of methods for detecting cyberattacks. Model-based solutions include statistical models and variants of state estimation techniques [20, 21]. Moreover, it has been suggested that Kalman sifting can be utilized for estimation assessment to identify cyberattacks [22, 23]. However, a useful framework was also mentioned. In order to identify fraudulent data injection attacks (FDI), supervised learning has been proposed [24,25]. Semi-supervised machine learning techniques, for instance, can take advantage of the spatial and temporal correlation of smart meter readings, whereas supervised machine learning techniques offer greater precision [26]. A few AI based arrangements have been proposed, for example, reward learning calculations and profound learning calculations. 28] Suggested connecting Fake Insusceptible Frameworks (AIS) and Backing Vector Machines (SVM) to identify malicious information. On the other hand, [29] proposes the advancement of stretch states. defense system based on estimates by using deep learning to extract nonlinear features from electric load data. Profound learning is additionally utilized in [30] to recognize misleading information infusion assaults continuously. In [31], real-time measurements from PMUs are also analyzed using deep learning for cyber-attack mitigation.

[32] also suggests a Repetitive Brain Organization (RNN) for detecting temporal variants within progressively verifiable data to identify digital attacks. Besides, [33] utilizes unaided profound figuring out how to propose a versatile wise assault identification arrangement. Medication, the Wellbeing System, and Insightful Organizations are only a couple of instances of establishments and organizations named by different significant level, persevering risk performers and programmer bunches [15]. Numerous solutions have emerged as a result of the smart grid's cyber threats' variety and complexity. A bibliographic examination and an outline of the most recent network protection answers for shrewd lattices is in this manner fundamental. In addition, there is no such analysis in the literature. On this topic, a

number of abstracts and research papers have already been distributed. For instance, manufactured examinations and outlines of organization security are given in [34, 35]. An efficient planning investigation of digital actual frameworks is likewise remembered for [36]. However, due to the fact that they were all published prior to 2016, these reviews are out of date and do not contain many of the newly proposed fixes. The authors then published their written examination reports [37, 38] that investigated various computerized risks in this large organization. However, neither did any of the articles investigate the attack detection techniques that were utilized nor conduct a bibliographic analysis of the relevant literature. An overview of sensible framework articles on network health is also included [39,40]. Despite focusing on cybersecurity standards, neither discloses the kinds of cyberattacks that are carried out nor the defenses that are used.

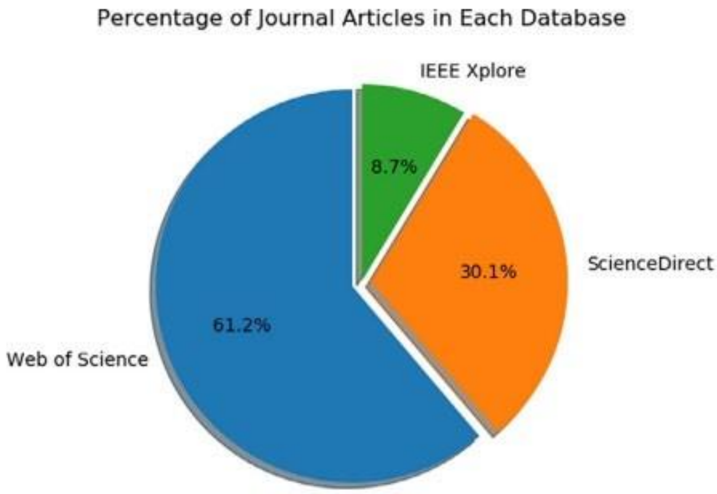

Figure 1: Percentage of journal articles published in each database on the topic of security systems in the smart grid.

From its introduction into the world to the present, the energy age, or the fundamentals of transmission and circulation, has progressed through numerous advancements, including numerous modifications and improvements. The power age's worldview is shifting from being entirely centralized to being decentralized. Traditional power grid structures cannot accommodate new requirements like robotic error and randomness checking, more efficient transmission, and challenges related to sustainable system combinations [1]. To address the prerequisites and difficulties, the Shrewd Matrix (SG) idea was created. Further improvement of the electrical lattice for SG requires many changes in charge choices and stream network innovation. The main idea was to use advances in data and communication to make electrical structures work better, last longer, and be more reliable [2].

The idea of shrewd metering (SM) is quite possibly of his most significant innovation empowering SG [3]. Not only do smart meters (SMes) enable customers to accurately, automatically, and more frequently communicate information about their energy use, but they also enable utility companies and customers to share information via two-way communication channels. Can be supplanted. This advantages the two shoppers and specialist co-ops. For instance, clients are bound to change exercises as indicated by energy costs, while suppliers benefit from remote inspecting, planning, separation/migration, diagnostics, blackout ID, authoritative issues, and weight the board objective setting. Can benefit from reducing expenses. Four]. Since each Assignment Structure Director (DSO) makes unique financial and mechanical decisions, the current situation is not uniform. To bring about these anticipated improvements, there are a few unresolved issues that need to be addressed. It has something to do with specific communications engineering in part. This satisfies essential requirements like accessibility and adaptability with uncompromising quality while enabling legitimate information exchange in a variety of settings, including urban, rural, and rural. In any case, every correspondence convention and climate have its own assets and shortcomings, so there is nobody size-fits-all arrangement.A diagram of the SG and SM conditions that influence the improvement of the SM system is presented in this article. In order to enhance the lattice behavior in SGs, we describe specific methods. In order to investigate potential approaches for Web of Things (IoT) conventions in SG environments, we discuss the potential evolution of SM foundations with IoT conventions in mind and concentrate on SM frameworks. In this instance, we propose a novel strategy that makes use of the Internet of Things. The main idea is to focus on possible enhancements in comparison to the progress that is currently in use and to suggest the deployment of progress that is enabled by the IoT in the context of SM. We are wondering how we can deploy autonomous aerial vehicles (UAVs) in rural and remote areas where other communication innovations are probably unimaginable or extravagant given the apparent lack of a suitable framework for media communication. We'll see if it can be used to broaden the application's reach. The proposed solution's viability is demonstrated by preliminary results that include actual field activities.

A perspective known as the Sharp Lattice was integrated into the standard power structure determined to further develop the manner in which age, transmission and flow networks collaborate. This includes using ICT and other methods to find faults and intrusions as well as simple monitoring of energy production, transmission, and distribution. However, more evolved features like programmed directionality, safety, adaptability, self-healing and mindfulness, continuous review, and similarities between layers are left out of current and previous interpretations of smart networks. This is me. On the other hand, the economysupporting digital communication infrastructure is also expanding, including large-scale machine-to-machine (M2M) communications and power generation and distribution networks based on artificial intelligence (AI) [18]. The AI can significantly support this type of applications, given the technology advances we are experiencing nowadays and the AI learning facilitators [16]. Notwithstanding correspondence framework in a multi-occupant framework, a stage coordinates simulated intelligence and IoT support and empowers cutting edge shrewd matrix support. The future Massive Internet of Things (MIoT) is one of the foundational components of the 5G/6G network factory. This paper's objective is to discuss the architecture as well as the challenges of the next generation of smart grids in terms of AIpowered smart grids and the integration of AI, IoT, and 5G for improved smart grids. to debate. It provides a comprehensive overview of the following trends and technical background in smart grid research. We also offer direction and potential solutions to some of the issues that are driving this new trend. Using soft tools like Matlab, NS2/NS3, Open-Daylight, and Mininet, as well as relevant literature, the implementation of the convergence of AI, IoT, and 5G for the discussed next-generation smart grid will be the primary focus of future research. Will be evaluated against. In order to produce and deliver energy to all customers, all utilities are adjusting. Splendid Grid (SG's) objective was to update the power network the board structure and its usefulness from the ongoing model to a further developed model. The measurement of user energy consumption, one of these functions, has already moved from regular manual measurements to more frequent automatic measurements in some countries, resulting in smart metering (SM). Increase. SM systems may benefit from technological advancements that make it possible to collect data about each user's energy consumption in more effective ways and distribute energy more evenly throughout the infrastructure. Instead of relying on sporadic communication slots, you can use a variety of communication contracts with this. This white paper explains the most important parts of SM network design, how they work, and how they can get better in the future. It explains the main technologies and protocols that can be used to exchange data across your infrastructure, as well as the advantages and disadvantages of each. Last but not least, as a potential enhancement to the SM framework, we suggest a brand-new arrangement. Low Power Wide Area Networks (LPWANs) are a collection of IoT communication technologies that form the foundation of this solution. These technologies may improve the performance and functionality of existing technologies. Unmanned aerial vehicles (UAVs) should also be used frequently to collect energy consumption data. This has a lot of obvious benefits, especially in rural and faraway places. We give some fundamental presentation results so we can evaluate the feasibility of the proposed procedure.

2. RELATED WORK

A chain of blocks with the same structure and records is called a blockchain. blocks are associated. The block links may be broken by minor alterations to the records within those blocks. It is likewise called state machine replication on the grounds that the blockchain is reproduced across an organization of hubs, with every hub sharing a piece of the organization. Overall, has two classes in blockchain. Blockchain with or without permission [4]. The public verifies transactions on the permissionless blockchain, and selected groups verify transactions on the permissionless blockchain. Regular systems are more centralized, but also faster and more scalable. In contrast, anyone can access a blockchain system without permission. Blockchain data cannot be changed at the time of its creation. EMR monitoring products currently on the market are described by the authors in [5]. The authors of [6] further elaborate on their ongoing research on blockchain technology. The resulting numbers show how much work is focused on different blockchain use cases. The Bitcoin framework has been the focus of consideration in more than 80% of documents, and less than 20% in contracts with other blockchain applications, including smart contracts and permissions. Most publications attempt to expose the privacy and security flaws and inefficiencies of blockchain systems. However, there is no clear picture or concrete evidence to support their claims. The authors explore some of the major blockchain protocols in [7]. In [8] the developer proposed his Hyperledger blockchain architecture, a popular open-source system that offers various pluggable features due to its design. Fuel blockchain innovation with a publicly accessible platform for maintaining transmitted data. This Linux-based phase has the potential to change the way the industry works. In fact, many blockchain products available on the market use his Hyperledger. The author of [9] talks about how IoT and blockchain can be combined to solve various problems and use cases. Applications of the shared digital economy have received the most attention in research. Additionally, many models are well thought out for blockchain and IoT development. A recording method was proposed by the authors in [10]. Patient-related data about medical services using Haze calculations. Using the work proposed in this document, medical records can be collected and input into our proposed blockchain framework. In [11], the authors continue to devote themselves to the further development of turbidity calculations so that experienced eHealth administrators can effectively process them. The author of [12] discusses the details, background, and evolution of blockchain, as well as the revolutionary impact it has had on his IT and non-IT industries. The authors of [13] conducted a thorough literature review to clearly convey the concepts and implications of blockchain technology. The author of [14] provides a more theoretical explanation of blockchain technology with examples and examples. The author of [15] talked about how the banking industry has improved privacy and security. The complex problems of autonomous and permissionless decentralized systems can be solved by using blockchain technology, providing the banking sector with a reliable solution for implementing security functions.

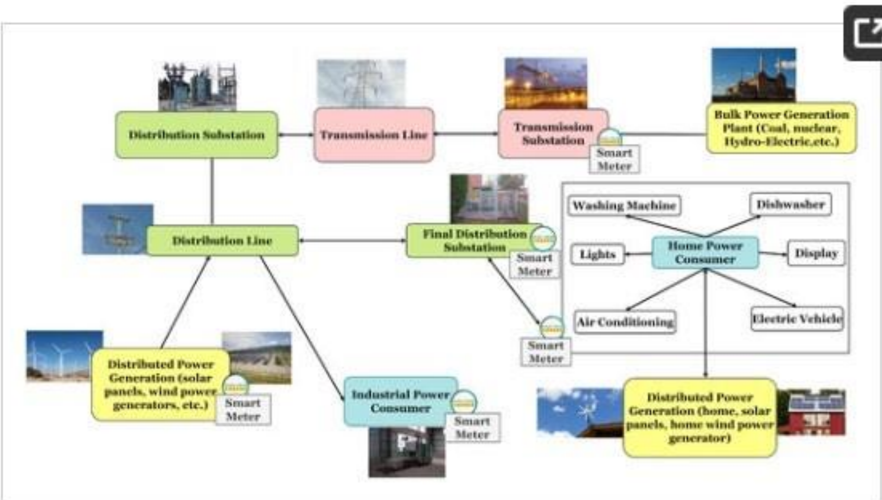

Figure 2: Smart Grid Electricity Flows.

The search terms used were Health Records, Health Systems, Health Care & System & Records, Health Care Blockchain to identify papers related to EHR literature search studies from various sources such as Google Scholar and ProQuest databases. . Limited citations to key research papers [8 and 11] allow this manuscript to provide a concise overview. As technology advances, we are required to demonstrate our willingness to preserve medical records. Obtaining hard copies is standard practice for the vast majority of US citizens (87%), and nearly half receive these documents from medical professionals [5]. However, EHR systems have various obstacles such as security, making it difficult for individuals to share information. Privacy and security implications for EHR systems were reviewed by Rezaeibagha et al. Examined. Information integration and sharing has been found to be an important aspect affecting information health security and privacy. The efficacy of the EHR system was recently reviewed by Afrizal et al. A review was conducted in which both individual and organizational perspectives were discussed. Constraints were exposed within the organization due to their report highlighting limited team interaction alongside inadequate senior management and skilled labor, and included in the personal constraints were limited access to computers as well as being unfamiliar with novel software. New technologies play a key role in easing obstacles, so removing hurdles in EHR systems can be achieved through several opportunities offered by Blockchain. Through blockchain technology we can ensure that all transactional data among participants in a network are consistently captured and stored in an immutable manner, and a completely distributed system means there's no single leader overseeing computational work on multi-computer transactional procedures. The use of Blockchain technology has the potential to enhance the United Nations' sustainable development objectives particularly in healthcare and modernization of public sector services like EHRs could be achieved through blockchain. Blockchain was studied as a possible solution for securing patient information within medical care systems by Zhang and his team, and examples of prioritizing the patient experience can be seen in safe data exchange environments. The use of blockchain technology is one way to improve health information management, as it improves oversight of opioid prescriptions and improves access to cancer-related patient records along with other health services such as telemedicine and insurance access. It's one. By examining patient health records, we demonstrated how blockchain is transforming the way medical information is shared.

A blockchain is a collection of blocks with a consistent layout and recording capabilities. Blocks are connected by links. Based on your input, you can break the connections between blocks by changing the datasets within those blocks. Because the blockchain is repeated in a network of nodes and each node has a stake in the network, it is also known as state machine replication. Blockchains fall into two broad categories. Blockchain [4], with or without permission. The public verifies transactions on the permissionless blockchain, and selected groups verify transactions on the permissionless blockchain. Regular systems are more centralized, but also faster and more scalable. In contrast, anyone can access a blockchain system without permission. Blockchain data cannot be changed at the time of its creation. EMR monitoring products currently on the market are described by the authors in [5]. The authors of [6] further elaborate on their ongoing research on blockchain technology. The resulting numbers show how much work is being focused on different blockchain use cases. The Bitcoin framework has been the focus of consideration in more than 80% of documents, and less than 20% in contracts with other blockchain applications, including smart contracts and permissions. Most publications attempt to expose the privacy and security flaws and inefficiencies of blockchain systems. However, there is no clear picture or concrete evidence to support their claims. The authors explore some of the major blockchain protocols in [7]. In [8] the developer proposed his Hyperledger blockchain architecture, a popular open-source system that offers various pluggable features due to its design. Fuel blockchain innovation with a publicly accessible platform for maintaining transmitted data. This Linux-based phase has the potential to change the way the industry works. In fact, many blockchain products available on the market use his Hyperledger. The author of [9] talks about how IoT and blockchain can be combined to solve various problems and use cases. Applications of the shared digital economy have received the most attention in research. In addition, many models are well thought out in terms of blockchain and his IoT development. A recording method was proposed by the authors in [10]. Patient-related data about medical services using Haze calculations. Using the work proposed in this paper, medical records can be collected and input into our proposed blockchain framework. In [11], the authors continue to devote themselves to the further development of turbidity calculations so that they can be effectively processed by experienced eHealth administrators. The author of [12] discusses the details, background and evolution of blockchain, as well as the revolutionary impact it has had on his IT and non-IT industries. The authors of [13] conducted a thorough literature survey to clearly convey the concepts and implications of blockchain technology. The author of [14] provides a more theoretical explanation of blockchain technology with examples and examples. The author of [15] talked about how the banking industry has improved privacy and security. The complex problems of autonomous and permissionless decentralized systems can be solved using blockchain technology, providing the banking sector with a reliable solution for implementing security features.

Despite being praised by Zhang et al as an ideal system for managing health records, however, there are few studies on a framework to use blockchain with patient records. One example of this is Fan et al's recommendation of a blockchain-based management information system for EHRs in response to concerns about privacy and security. Six modules including ledger database committer orderer endorser and client form the basis of their framework, but the concepts of digital currency or issues around personal data were not given a significant amount of attention by the group led by Fan. They left these subjects for future examination to aid in Fan et al.'s efforts Griggs and colleagues worked on addressing security concerns that arose when using blockchain by implementing a private network. Through its endurance as a record keeping system, Block captures both the prior and current states of J and K. Sadeghi RTwo kinds of transactions are available: public and private, and Griggs and other experts have shown that opting for private blockchains could be an effective way to address privacy issues related to personal data management in the healthcare sector. Privacy worries may impact how often people choose to opt-in to EHR systems.

By applying soft systems methodology in their study, Sharma and co-authors furnished qualitative evidence showing that employing blockchain to share EHRs enhances patient involvement opt-in percentages, and their attention was fixated on the Precision Health Care (PHC) program--an assembly of personal EHRs intended for universal access and to advance overall health in society. The proposal for a blockchain-based system was demonstrated to improve trustworthiness in unreliable PHC platforms and aid in improving communication by allowing for better access to patient records. Esmaeilzadeh and Mirzaei investigated how blockchain might influence HIE and their research shows that the primary reason users would prefer a blockchain-based system is because of its ability to protect their privacy. The aim of Shahnaz and colleagues was to streamline blockchain integration into EHR and outlined a plan to address versatility concerns when utilizing blockchain through proposed structural changes. By utilizing a blockchain platform in the medical industry there arises a mix of advantages and disadvantages that could be investigated more extensively down the line. The role of blockchain technology in health care remains unclear despite several recent studies exploring how this technology could benefit health information management, but until now this has been the most significant research on how blockchain technology affects patient's intention to exchange their clinical data through mediation. The lack of research into extrinsic motivations and security perceptions has created significant gaps in our understanding of how these factors affect healthcare provider's information systems.

3. METHODOLOGY

Our study aims at identifying the potential benefits and challenges of implementing blockchain technology in the medical care industry, and this part of the paper elucidates the methodological design utilized for conducting the study. Fig and to conduct this review we went through four main processes which include extraction & pre-processing of the data set along with its examination & perception. If you're looking for data on the intersection of blockchain tech and healthcare industry according to their indexation in WoS and Scopus between years 2016 to 2020, look no further than this dataset, as in order to conduct a bibliometric analysis on blockchain technology within the healthcare industry sector, this study utilized an open-source statistics program called R. Installed on the R desktop system and being used is the package, which numerous fields of study have employed this bibliometrics technique for exploration.

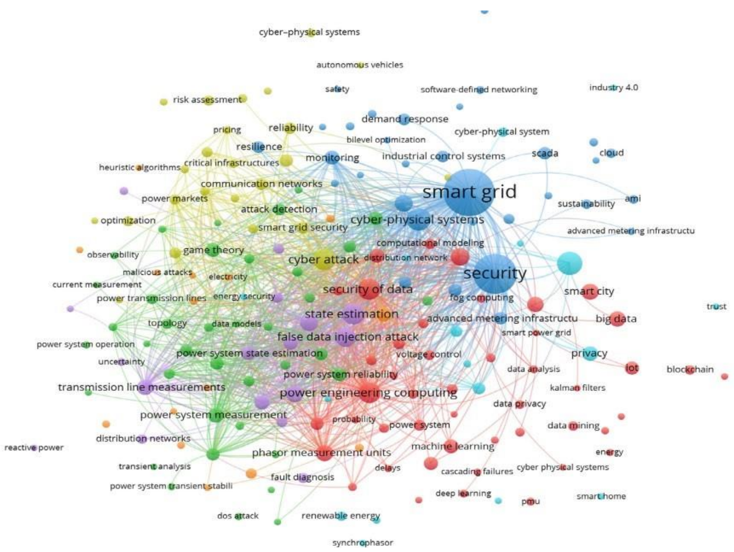

Figure 3: A heat-map of keywords mentioned in all journal articles in the subject of smart grid cybersecurity.

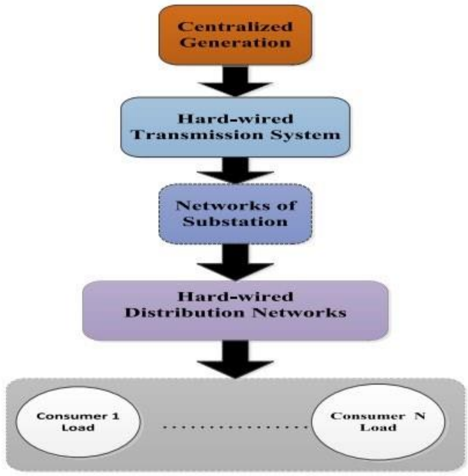

Figure 4: The classical grid block diagram.

To find articles that included the phrase "blockchain in medical services" in their titles, watchwords, or modified compositions, this paper conducted a literary survey. The review of previous work focused on locating areas in healthcare management where blockchain has been used or proposed to be used. The EBSCO database, the Web of Science, the Applied Science & Technology Source, and several other online resources, such as ResearchGate and Google Scholar, were used to select the papers. To conduct a review outlining the advantages and disadvantages of blockchain-based technology in the healthcare sector, forty most recent manuscripts from selected papers published between 2016 and 2020 were selected. Only English-language written articles were included, and health-related journals received preference. The survey's findings provide a clear understanding of blockchain capabilities and a list of how they affect the operation of medical care associations. The results also highlight a dearth of research and application-based effort on the subject.

3. RESULTS AND DISCUSSION

Blockchain innovation brings efficacy and discovery to clinical preparation. These data records can be stored on the blockchain as intelligent contracts of digital fingerprints. Advantages of using blockchain technology in the medical field include consistent authorization patterns for access to electronic health information, identification and authentication of all participants, security of the network and his infrastructure at all levels. will be Blockchain is used to monitor drug supply chains and track drug liability. This technology can be used to store information about individual patients, thus helping to analyze and validate the results of specific procedures. Blockchain is not only used to improve security, increase information visibility and transparency, but also for clinical trials, patient monitoring, and maintaining health records. Keep your hospital financial reports up to date and reduce the time and money spent on data conversion. In an information-driven environment, several problems are solved. Blockchain innovations hash individual blocks of patient health records. Patients are also encouraged to provide necessary data to third parties while keeping their identities private through the blockchain system. It is expected that the vast number of informational indicators will lead to preliminary clinical studies. Experts focus on these information indicators and conduct routine experiments to investigate, evaluate and find productivity ratios under different conditions. Information will be analyzed, and further decisions will be made based on these findings. Nonetheless, many researchers can control the information and evidence collected to alter their results.

Additionally, many pharmaceutical companies want to record insights that are useful to their business. Therefore, researchers are using blockchain technology to simplify clinical trials and ensure fairness. Helps record clinical trials safely, unevenly, and easily. The information collected may provide post-market analysis to improve patient care and maximize efficiency benefits. Open management of blockchain technology, transparent audit trails, data transparency, robustness, increased privacy, and security form the basis of these standards. This will enable healthcare providers to comply with current medical standards, including drug safety. A key aspect of this new industry focuses on why blockchain technology should be used in the healthcare sector and the unresolved issues that complicate its use. Table 10 presents different angles of inspiration and challenges in implementing collaborative blockchain efforts in response to the healthcare industry. The pros and cons of blockchain use by healthcare companies are detailed.

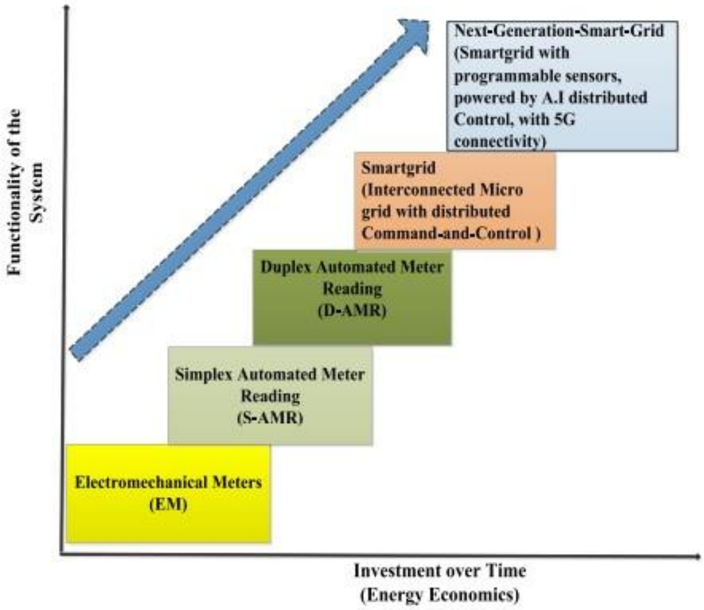

Figure 4: The evolution from the traditional grid to next generation smart grid

• Motivations

Blockchain technology is the result of modern society's efforts to meet requirements in numerous healthcare industry applications. Using blockchain technology, system security goals can be maintained while patient quality is effectively improved. A review of the studies is used to explore, identify, and categorize the various benefits and motivations for using blockchain technology in healthcare. Additional discussion shows these categories of motivation.

➢ Decentralization

By distributing medical data across the network rather than at a single central location to prevent a single point of security failure, the use of blockchain has significant advantages for medical data. This biological system considers decentralized responsibility for data, hence requiring all partners in the medical care industry to have consistent, secure, and moment admittance to this information. In addition, this strategy makes it possible to transmit and manage medical information under the control of an algorithm that uses a consensus mechanism based on feedback from trusted network members. A decentralized network has replaced the traditional ecosystem of the healthcare industry, such as RPMs, tele dermatology, telesurgery, EHRs, EMRs, and PHR systems. By overcoming several problems, including those relating to patient records, the interchangeability of medical data, and the safety of healthcare organizations and medical care services, this change has provided the healthcare industry with numerous advantages.

➢ Universal interoperability and standardization issues

Blockchain is still in the beginning phases and is quickly advancing, which is the reason no settled norm for it is accessible yet. The execution of blockchain innovation in the medical care area would likewise take additional time and exertion for the association to embrace because of the requirement for worldwide ensured normalization. The standard permit would benefit from settling on the size of the information, the information design and the sort of information that could be put away on the blockchain. Based on established standards, which could be easily implemented within organizations, the adaptation of blockchain would become simpler.

- Healthcare organization skill issues

The idea of a blockchain innovation plan of action is known to not many individuals. For hospitals or any other healthcare organization, completely converting to blockchain technology the conventional RPM, EHR, PHR, and EMR infrastructure would take a long time.

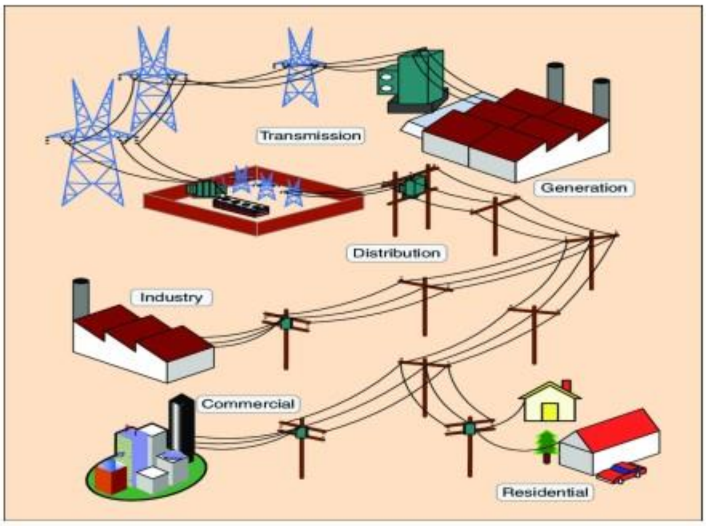

Figure 5: A classical grid

Validity and discoveries are brought to clinical preliminary testing by blockchain innovation. These records can be stored in the digital thumbprint as intelligent contracts on Blockchain. A couple of the benefits of involving Blockchain Advancements in Medical services incorporate uniform examples of approval to get to electronic wellbeing data, character confirmation and verification for all members, and organization framework security at all levels. The drug store network is checked, and medicine liabilities are followed utilizing Blockchain. Because it can be used to store information about each individual patient, this technology assists in analyzing and validating the outcomes of a particular procedure. Blockchain is used for clinical trials, patient monitoring, and health record maintenance, as well as to enhance safety, display information, and transparency. It reduces the amount of time and money spent on data transformation while maintaining the accuracy of hospitals' financial statements.

In the data centered environment, it settles a couple of issues. Blockchain development will make a hash for individual blocks of patient prosperity records. The blockchain system would also encourage patients to share necessary data with third parties while concealing their identities. A vast number of educational files is supposed to play out a clinical starter. To provide examinations, evaluations, and productivity proportions under various conditions, the specialists concentrate on these informational indices and carry out routine trials. The data is analyzed, and additional decisions are made considering these findings. In any case, various analysts have some control over the data and verification gathered to change the result. In addition, a lot of pharmaceutical companies want to keep track of the findings that will help their companies. Consequently, researchers use Blockchain technology to simplify clinical studies and guarantee fairness. It will aid in the straightforward, secure, and uneven recording of clinical trials. Post-market analysis to maximize efficiency benefits can be provided by the collected data, which has the potential to improve patient care. These standards are based on Blockchain technology's improved privacy and security, open management, transparent auditing tracks, data transparency, robustness, and openness. As a result, healthcare providers can adhere to the most recent healthcare standards, which also include safeguarding pharmaceutical supplies.

5. CONCLUSION

Because of its inborn encryption and decentralization, Blockchain can be imaginatively utilized in clinical benefits. It aids in the production of counterfeit medications for combat, advances the adaptation of health data, expands interoperability among medical service organizations, and enhances the security of patients' electronic clinical records. Numerous medical service industries could be transformed by blockchain technology; One of Blockchain's most significant applications is advanced arrangements made conceivable by astute agreements in regions like medical services. Smart agreements will reduce costs by eliminating intermediaries from the installment chain. The potential of Blockchain in healthcare is significantly influenced by the ecosystem's adoption of related advanced technologies. System tracking, medical insurance, and clinical trials are all part of it. Hospitals can chart their services using a Blockchain framework by using device tracking throughout the life cycle. Blockchain technology can effectively be used to accelerate clinical activities with improved information support by further developing executives' patient histories, particularly during the protection intervention process. Generally, this innovation would essentially upgrade and ultimately alter the treatment, use, and arrangement of medical care administrations for patients and doctors. The technology known as blockchain has the potential to change industries. It might be able to make the current systems very secure and hard to break into. The medical services area is one of the businesses where how much information is quickly developing. To improve healthcare, technologies like Blockchain are needed to store data in a secure manner, allow for analysis, and make it simple to efficiently track records. By valuing Blockchain technology, the medical services sector has a great opportunity to advance its innovation. A medical care implementation of Blockchain innovation was the proposed work.

This work is constrained by the databases that we searched. Additionally, an increase in blockchain-related activities in the healthcare industry has impacted the study's timeline. The purpose of this study, on the other hand, is to determine the gap between blockchain and the healthcare industries by evaluating the extensive blockchain research that has been carried out on them thus far. In the healthcare field, numerous academics have studied blockchain technology. In this investigation, medical care studies and the blockchain were the focus of bibliometric analysis. This study significantly affects how the healthcare sector develops. The conclusion is comprised of the statements below:

- This work presents a few all-inclusive examination periods of blockchain, and medical care industry exercises directed by researchers and associations. Scholars use blockchain to solve problems in the healthcare industry, according to the analysis of data distribution, keywords, research area, venues, and citations.
- Case investigations of blockchain use in medical care, like TMIS and Health framework, were directed.

- This concentrates on talking about the inspiration for researchers and analysts and featured the difficulties that can be looked in the investigation of blockchain in the medical services enterprises.

- There are numerous research opportunities for researchers and organizations, including the process of sharing health data, clinical trials, the pharmaceutical industry, updating and accessing big data, artificial intelligence, a 5 G ultrasonic device, security, and privacy. H.M. Hussien and others

EHR systems are a significant and useful healthcare information technology application. It is known that such technology significantly boosts an organization's performance when utilized effectively. Because they reduce medical errors and maximize costs, electronic health record (EHR) systems are advantageous to health networks [4]. Despite such benefits, some medical services suppliers are delayed utilizing EHR frameworks [4] because of seen obstructions, for example, those including patient choices [10]. The presence of additional challenges may manifest in concerns over safety measures or a necessity for increased amounts of time being spent on certain tasks. Through this investigation, it was discovered that implementing blockchain technology could provide a feasible solution to managing concerns over data security and improving patient involvement in managing their healthcare information. The precise function of blockchain technology in healthcare systems is yet to be determined.

This study added to the body of knowledge regarding management information systems in healthcare that use blockchain technology to protect health records. The use of blockchainbased systems for sharing health records is linked with patients' willingness as per the empirical findings, and a blockchain-enabled framework can drive the sharing of patient health data by providing digital tokens as rewards within an ecosystem comprising doctors and other healthcare professionals. In the context of sharing health records via a blockchain-based mechanism, patients exhibited optimistic views toward safeguarding their sensitive information, and this is supported by the CRediT statement by J. Conceptualizing a software project is typically led by someone like Victor R Prybutok and in this case, he also provided research support for validation. But review & editing were likewise part of his workload, whereas Kiarash Sadehi. R worked on development aspects like coding among other tasks while Writing - Editing & Reviewing are some of Brian Sauser's expertise areas which are combined with his proficiency for tackling challenges related to project management, research methodology & utilization of resources.

As a result, it is possible to make the most of the existing telecom infrastructure rather than relying on specialized ones. The fundamentals of SM network design as well as its development are discussed in this article, with an emphasis on future enhancements. It explains the main technologies and protocols that can be used to exchange data across your infrastructure, as well as the advantages and disadvantages of each. Last but not least, as a potential enhancement to the SM framework, we suggest a brand-new arrangement. The plan depends on a set-up of Low Power Wide Region Organization (LPWAN) correspondence innovations for the Web of Things (IoT) [17] - [19] that can be utilized to more readily address current turns of events and give extra capacities. Furthermore, we propose utilizing a PC helped Ethereum vehicle (UAV) to gather energy utilization information discontinuously. This enjoys clear benefits, particularly in provincial and distant areas. In order to determine whether or not the suggested strategy is a viable one, we provide some preliminary performance data.

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SMART GRID APPLICATIONS AND BLOCKCHAIN TECHNOLOGY IN THE AI ERA

***Ramiz Salama*[1], *Chadi Altrjman*[2,3], and *Fadi Al-Turjman*[2,3]**

[1]Department of Computer Engineering, AI and Robotics Institute, Research Center for AI and IoT, Near East University Nicosia, Mersin 10, Turkey

[2]Artificial Intelligence Engineering Dept.,
AI and Robotics Institute, Near East University, Nicosia, Mersin 10, Turkey

[3]Research Center for AI and IoT, Faculty of Engineering, University of Kyrenia, Kyrenia, Mersin 10, Turkey

ramiz.salama@neu.edu.tr, Fadi.alturjman@neu.edu.tr, Fadi.alturjman@kyrenia.edu.tr

Abstract: The integration of Smart Grid Applications and Blockchain Technology has emerged as a potential solution to enhance energy management's efficiency, security, and transparency in the energy industry. Smart Grid Applications utilize advanced technologies to optimize the generation, distribution, and consumption of electricity, while Blockchain Technology offers a decentralized and distributed ledger system that can facilitate secure and transparent transactions. This review paper analyses the existing literature on Smart Grid Applications and Blockchain Technology to identify the potential benefits and challenges associated with their integration in the energy industry. The key benefits of this integration include the ability to facilitate secure and transparent transactions, enable peer-to-peer energy trading, and support the integration of various Distributed Energy Resources (DERs) into the grid. However, challenges associated with the lack of standardization, interoperability issues, and scalability concerns associated with blockchain technology need to be addressed. The successful implementation of Smart Grid Applications and Blockchain Technology in the energy industry will require collaboration between industry stakeholders, regulators, policymakers, and standard-setting organizations. Future research is needed to explore the potential of these technologies in addressing specific energy management challenges. The findings of this review suggest that integrating Smart Grid Applications and Blockchain Technology can transform the energy industry and create new opportunities for innovation.

Keywords: Smart Grid, Blockchain Technology, Decentralization, Distributed Energy Resources (DERs), Energy Trading.

1. Introduction

Integrating Smart Grid Applications and Blockchain Technologies can revolutionize the energy industry by providing a more efficient, secure, and transparent platform for energy management, especially in the artificial Intelligence (AI) era. AI can significantly support this type of application, given the technological advances we are experiencing nowadays and the AI learning facilitators [1]. The Smart Grid integrates various Distributed Energy Resources (DERs), including renewable energy sources, energy storage systems, and electric vehicles, into the grid. On the other hand, Blockchain technology offers a decentralized and distributed ledger system that can facilitate secure and transparent transactions without intermediaries. By combining these technologies, energy trading and management can be more streamlined and automated, allowing for peer-to-peer (P2P) energy trading, smart contracts, and grid management.

Additionally, using blockchain technology in the energy industry can help enhance cybersecurity and ensure interoperability between various systems and technologies. The growing energy demand, the increasing adoption of renewable energy sources, and the need for efficient energy management have led to significant changes in the energy industry. Smart Grid Applications and Blockchain Technology are emerging as potential solutions to enhance energy management's efficiency, security, and transparency.

Smart Grid Applications utilize advanced technologies such as sensors, communication networks, and data analytics to optimize electricity generation, distribution, and consumption. Integrating Smart Grid Applications can improve the reliability and resiliency of the energy grid and enable more efficient management of energy resources.

Blockchain Technology, on the other hand, offers a decentralized and distributed ledger system that can enhance the security and transparency of energy transactions. Using blockchain technology in the energy industry can facilitate secure and transparent transactions, enable peer-to-peer (P2P) energy trading, and support the integration of various Distributed Energy Resources (DERs) into the grid. The integration of Smart Grid Applications and Blockchain Technology has the potential to transform the energy industry and create new opportunities for innovation. However, implementing these technologies in the energy industry faces several challenges that must be addressed. These challenges include the lack of standardization, interoperability issues, and scalability concerns associated with blockchain technology. Furthermore, regulatory and policy frameworks need to be developed to support the implementation of these technologies in the energy industry. In this review paper, we aim to analyze the existing literature on Smart Grid Applications and Blockchain Technology to identify the potential benefits and challenges associated with their integration in the energy industry. We discuss the key benefits, including secure and transparent transactions, P2P energy trading, and support for DERs, and identify the challenges that need to be addressed to ensure the successful implementation of these technologies. Finally, we provide recommendations for future research and policy development to support the integration of Smart Grid Applications and Blockchain Technology in the energy industry.

Amount of Previously Published Work

The topic of Smart Grid Applications and Blockchain Technology has gained increasing attention in recent years, with a growing number of research papers, articles, and reports published on the subject. A search on academic databases, such as IEEE Xplore, Google Scholar, and ScienceDirect, reveals a significant body of work on the topic. These studies explore the potential benefits and challenges associated with the integration of Smart Grid Applications and Blockchain Technology, and investigate various use cases of blockchain technology in the energy industry, including P2P energy trading, smart contracts, and grid management. Moreover, several research studies have focused on addressing the cybersecurity and interoperability concerns associated with the integration of these technologies. Overall, the significant amount of previously published work on Smart Grid Applications and Blockchain Technology highlights the growing interest in these technologies and their potential to transform the energy industry.

Applications for Smart Grids and Blockchain Technology

In this review paper, we searched academic databases, including IEEE Xplore, Google Scholar, and ScienceDirect, using the keywords "Smart Grid Applications" and "Blockchain Technology." The search was conducted in May 2023, and we included studies published between 2018 and 2023. We excluded studies that were not written in English or were not available in full text.

We analyzed the selected studies to identify the potential benefits and challenges associated with the integration of Smart Grid Applications and Blockchain Technology, as well as the various use cases of blockchain technology in the energy industry. We also examined the cybersecurity and interoperability concerns associated with the integration of these technologies. The studies were analyzed and synthesized to provide an overview of the current state of research on the topic and to highlight the key considerations for successful implementation of Smart Grid Applications and Blockchain Technology in the energy industry. The quality of the selected studies was evaluated based on their relevance to the research questions, methodology, and data analysis. We used a narrative synthesis approach to analyze and synthesize the findings of the selected studies. The results of the analysis were presented in the form of a narrative review, which provides a comprehensive overview of the current state of research on Smart Grid Applications and Blockchain Technology.

2. Discussion

The results of our review indicate that Smart Grid Applications and Blockchain Technology offer significant potential for transforming the energy industry by enhancing the efficiency, security, and transparency of energy management. The key benefits associated with the integration of these technologies include the ability to facilitate secure and transparent transactions, enable P2P energy trading, and support the integration of various Distributed Energy Resources (DERs) into the grid. However, the implementation of Smart Grid Applications and Blockchain Technology in the energy industry faces several challenges that need to be addressed. The lack of standardization and interoperability issues between different blockchain platforms are significant challenges that need to be addressed. Additionally, the scalability concerns associated with blockchain technology may limit its adoption in largescale energy systems. Furthermore, the regulatory and policy frameworks need to be developed to support the implementation of these technologies in the energy industry. Addressing these challenges will require collaboration between industry stakeholders, regulators, policymakers, and standard-setting organizations. Furthermore, there is a need for further research to explore the potential of these technologies in addressing specific energy management challenges, such as demand response and energy storage.

Overall, integrating Smart Grid Applications and Blockchain Technology can transform the energy industry by improving efficiency, security, and transparency. However, successful implementation will require addressing the challenges identified in this review, developing supportive regulatory and policy frameworks, and further exploring the potential of these technologies in addressing specific energy management challenges. The potential benefits of integrating Smart Grid Applications and Blockchain Technology in the energy industry have been widely recognized in previous studies, and our review confirms this trend. In particular, the secure and transparent transactions enabled by blockchain technology and the P2P energy trading enabled by smart grid applications have been highlighted as significant benefits. Additionally, integrating DERs into the grid is seen as an important way to improve energy management efficiency. However, the challenges associated with the implementation of these technologies cannot be ignored. Standardization and interoperability issues between different blockchain platforms and scalability concerns have been identified as the main challenges that need to be addressed. Furthermore, the regulatory and policy frameworks need to be developed to support the implementation of these technologies in the energy industry.

To overcome these challenges, industry stakeholders, regulators, policymakers, and standard-setting organizations must collaborate to develop solutions. Further research is also needed to explore the potential of these technologies in addressing specific energy management challenges, such as demand response and energy storage. Overall, the integration of Smart Grid

Applications and Blockchain Technology has the potential to transform the energy industry by improving efficiency, security, and transparency. However, successful implementation will require addressing the challenges identified in this review, developing supportive regulatory and policy frameworks, and further exploring the potential of these technologies in addressing specific energy management challenges [17]-[18].

3. Results

Our literature review identified a significant body of work on the potential benefits and challenges associated with integrating Smart Grid Applications and Blockchain Technology. The studies analyzed in this review highlight the potential of these technologies to transform the energy industry by enhancing energy management's efficiency, security, and transparency. The key benefits associated with integrating Smart Grid Applications and Blockchain Technology include facilitating secure and transparent transactions, enabling P2P energy trading, and supporting integrating various Distributed Energy Resources (DERs) into the grid. Moreover, blockchain technology offers a decentralized and distributed ledger system that can enhance the cybersecurity of the energy grid. However, several challenges need to be addressed to ensure the successful implementation of these technologies in the energy industry. These challenges include the lack of standardization, interoperability issues, and the need to address the scalability concerns associated with blockchain technology. Additionally, the regulatory and policy frameworks need to be developed to support the implementation of Smart Grid Applications and Blockchain Technology in the energy industry. Overall, the studies analyzed in this review demonstrate the potential of Smart Grid Applications and Blockchain Technology to transform the energy industry. However, successful implementation will require addressing the challenges identified in this review and developing a supportive regulatory and policy framework.

Recent studies have also demonstrated the potential of Smart Grid Applications and Blockchain Technology to support the transition to renewable energy sources. By facilitating P2P energy trading and enabling the integration of renewable energy sources into the grid, these technologies can reduce the reliance on traditional energy sources and support the growth of renewable energy markets. Furthermore, the use of blockchain technology can enable the development of new business models, such as virtual power plants and energy communities, which can enhance the efficiency and resilience of the energy system. Another significant challenge that needs to be addressed is the energy consumption associated with blockchain technology. The energy-intensive process of verifying and adding new transactions to the blockchain has raised concerns about the environmental impact of blockchain-based energy systems. Nevertheless, recent research has proposed several approaches to address this issue, such as using renewable energy sources for mining and developing more energy-efficient consensus algorithms. Overall, the integration of Smart Grid Applications and Blockchain Technology has the potential to revolutionize the energy industry by enhancing the efficiency, security, and transparency of energy management, supporting the transition to renewable energy sources, and enabling the development of new business models. However, the successful implementation of these technologies requires addressing the identified challenges and developing a supportive regulatory and policy framework.

4. Conclusion

In conclusion, our review of the literature indicates that the integration of Smart Grid Applications and Blockchain Technology offers significant potential for transforming the energy industry by enhancing the efficiency, security, and transparency of energy management. The key benefits associated with the integration of these technologies include the ability to facilitate secure and transparent transactions, enable P2P energy trading, and support the integration of various Distributed Energy Resources (DERs) into the grid. However, the implementation of Smart Grid Applications and Blockchain Technology in the energy industry faces several challenges that need to be addressed. These challenges include the lack of standardization, interoperability issues, and scalability concerns associated with blockchain technology. Addressing these challenges will require collaboration between industry stakeholders, regulators, policymakers, and standard-setting organizations. Overall, the integration of Smart Grid Applications and Blockchain Technology has the potential to transform the energy industry and create new opportunities for innovation. However, successful implementation will require addressing the challenges identified in this review and developing a supportive regulatory and policy framework. Further research is needed to explore the potential of these technologies in addressing specific energy management challenges.

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