ECG IMAGE ANALYSIS FOR ARRHYTHMIA DISEASE USING DEEP LEARNING

Sharu Priya S
Dept of Computer Science and Engineering
IFET College of Engineering
Villupuram,India

Mr Jayakumar D
Associate Professor,Dept of Computer Science and Engineering
IFET College of Engineering
Villupuram,India

ABSTRACT The analysis of electrocardiogram (ECG) data categorization is crucial for the systematic identification of coronary artery disease. It is common to divide the two steps of feature extraction and pattern categorization into two segments. Recent studies have found that deep neural networks are more adept than experienced cardiologists at detecting cardiac arrhythmias. These networks were taught on huge amounts of data. Recent developments in artificial intelligence are to blame for this. Deep convolutional neural networks are used inthis study's technique for classifying ECG rhythms (CNN). For the CNN to identify and eventually generalize the different ECG arrhythmia types, as data provided, the wavelengths of the different kinds of arrhythmia were employed. The classification results show that the suggested CNN model, when trained and tested on ECG samples MIT-BIH arrhythmia collection, with a median level of precision of 99.9%. The most precise and effective tool is the classification. Additionally, a CNN model and a deep neural network model were contrasted. According to comparative statistics, the superior to the existing classifier was able to obtain a 90.93% mean accuracy. It is thus demonstrated the CNN classifier under consideration, which uses import ECG spectral images, may improve categorization accuracy without additional human which was before of the ECG data.

Keywords—Electrocardiogram (ECG); arrhythmia classification; cardiovascular diseases (CVDs); convolutional neural network (CNN).

I. INTRODUCTION

One of the main illnesses that endanger human living is cardiovascular disease. According to the World Health Organization, cardiovascular diseases (CVDs) is presentlythe primary factor of fatalities. A staggering 17.9 million people, or almost 31% of all demises, were brought on by CVDs. In impoverished countries, more than 75% of these deaths occurred. Additionally, Cardiovascular disease (CVD) encounter and passing away are both gradually rising. As a consequence, frequent cardiac rhythm monitoring is more important than ever for the treatment and prevention of CVDs. Arrhythmias are a sizable collection of diseases associated with cardiovascular disease. Arrhythmia can arise independently or in tandem with other cardiac disorders. A crucial aspect of diagnosing a tachycardia is the ECG (electrocardiogram). The heart's excitement, transport, and recuperation are recorded using this crucial element of current healthcare equipment is the electrocardiogram, also known as an ECG.

Automatic detection of heart rhythm anomalies using ECGdata is essential for the digitalized identification of cardiovascular disease. The several kinds of heartbeats— normal beat (NOR), left bundle branch block beat (LBB), rightbundle branch beat (RBB), premature ventricular contraction beat (PVC), and atrial premature contraction beat (APC) whichhad been represented by the moment features extracted created by the rapid Fourier transform. The CNN identified and classified the various ECG arrhythmia types using an analysis of the five main kinds of arrhythmia. Deep Learning (DL) is the study of gathering knowledge, making forecasts, choosing, or using a collection of facts, referred as practice data, torecognize Complex structures. Since Enhanced precision isfrequently achieved through merely expanding the size of the workout records, CNNs are higher adaptable than conventional learning algorithms. Multiple current versions of decision treesand support vector machines (SVMs) are inefficient, necessitating more research to achieve generalization of the results and more physical work to characterize prior knowledge. The widespread usage of the convolutional neural network (CNN), including image processing and time series analysis, is a well-known and more advantageous image categorization model. It has a feed-forwarding architecture with many interconnected levels. The full connected layer is in charge of data classification, while convolutional and hidden layers are essential for feature extraction. The spectral images of the different arrhythmia types were used to process the CNN in order to recognize and ultimately categorize the ECG arrhythmia types. The classification is the most accurate and efficient. Additionally, a CNN model and a deep neural network model were compared. As a result, it has been demonstrated regarding the CNN classifier under consideration, which uses ECG audio signals as input, may improve categorization precision without the use of manuals which was before of the ECG data.

The following areas of study have benefited from this work:

1. Suggested techniques made use of massive amounts of Dataset from MIT-BIH
2. Suggested CNN which classify arrhythmias using five distinct methods to identify them.
3. Suggested to diagnose arrhythmia illness, CNN used features and classifiers.
4. Compared and analyzed the accuracy of proposed CNN and other existing approaches

II. LITERATURE REVIEW

Only papers that employ machine learning to predict the categorization of arrhythmia from the most recent few yearswere included in the literature survey or review.

Deep learning techniques: The study of information retrieval, predicting, making decisions, or using a body of facts, referred to (DL). DNN are more flexible than conventional learning algorithms because high precision is frequently attained by merely expanding the training dataset. Many modern versions of Decision trees and support vector machines (SVMs) are inefficient, prompting more study to achieve generality and more physical work to characterize prior knowledge.

Multilayer perceptron: The supervised neural network variety known as the multilayer perceptron (MLP) has the capacity to understand complicated platforms. The structure of the MLP is intricate due to the presence of numerous hidden layers and layers of neurons that are linked to one another in a feed-forward fashion. Every cell should density that is given to it for a process that iteratively cycles through its inputs.

Deep Belief Network: In 2006, Hinton suggested using numerous levels of the Restricted Boltzmann Machine in Deep Belief Networks (DBNs). This network is a potent automated method that has been applied repeatedly to depict various types of dynamic random variables. By using a Limited Boltzmann Machine, that layers are created. Every Restricted Boltzmann Machine (RBM) takes the prior inputs and sends them into a specific layer of theRBM in the following layer. By layer-by-layer teaching the Limited Boltzmann Machine from the bottom up, DBNs are trained. RBM is a single-directed design that can be effectively used to describe binary random number distributions for data in binaries.

Recurrent Neural Network(RNN): RNN enable the platform to remember previous input, allowing decisions to be based on prior information. This makes them a very popular model for categorizing a single input in a sequence and studying time series data. In order to improve the outcome usingadditional values, it provides the system with both the prior value and the present value once more. RNN improves the buried layer and generates classification by utilizing a dataat each stage.

(A) Long Short-Term Memory (LSTM): Feedback links form the foundation of the LSTM, a special kind of RNN. It may be made use of to analyze a single data point in a sequence to search for abnormalities. Data from time series can be anticipated and modeled using technique.

(B) Bidirectional Recurrent Neural Network (BRNN): Two concealed levels that are at odds with one another are connected by BRNNs to a particular output. The output layer in this kind of dynamic deep learning includes input from both the past and the present. In the BRNN working paradigm, there are two sets of RNN neurons: an upward phase and a reverse phase, respectively.

(C) Gated Recurrent Unit (GRU): In addition to being an alternative to RNN, the GRU version of RNN provides better processing efficiency than the LSTM. In other terms, GRU's complexity is lower and its architecture is easier because it has fewer layers than LSTM. The crucial element of the GRU are the entryways (data entryways and ignore entryways), which help tobalance the information transformation. Update gates combine income and outcome gates and are crucial for adjusting activation.

Additionally, experts are working to further integrate this proposed strategy with practical artificial intelligence- based methods, according to optimization, metaheuristics, machine learning, and deep learning. These methods also provide procedures based on security to guarantee safe client– server contact.

(D) ARRHYTHMIA DATASET

There has been usage of the MIT-BIH Arrhythmia Collection at about 500 locations globally since it was first made available in 1980 for both basic research into cardiac dynamics and as the initial set of typical tests for evaluating arrhythmia monitors that are accessible to everyone. Neither of its creators could have anticipated how long it would last. This experience has had a significant influence on the understanding currently held about the utility of shared resources for applied and fundamental studies and the creation and assessment of medical devices. This experience, combined with the American Heart Association Database, had an intriguing impact on motivating arrhythmia detector makers to compete on the premise of directly quantifiable performance.

The approximately 4000 for decades Holter samples that the Beth Israel Hospital Arrhythmia Laboratory collected in between 1975 and 1979 constitute the foundation for the ECG found in the MIT-BIH Arrhythmia Registry. A samples came from patients in just over 60% of the cases. 22 randomly chosen records (which are categorized 100 to 124 inclusively with certain ones lacking) from this set are present in the record set, along with twenty-five additional entries chosen a range of uncommon although functionally relevant events thatwould not be adequately reflected due to a tiny proportion of Holter transcriptions were included from an identical set. The 48 cassettes are each slightly over 30 minutes long.

TABLE I

THE ECG DATASET WHICH INCLUDE BOTH PRACTICE AND EVALUATING DATASET

Types of Arrhythmia	*Data Records*	*Practice Set*	*Evaluating Set*
NOR	*100,105,214*	*445*	*86*
LBB	*109,111,213*	*445*	*86*
RBB	*118,124,210*	*445*	*86*
PVC	*106,219*	*445*	*86*
APC	*207,209,227*	*445*	*86*

Samples for NOR were taken from tapes 100, 105, and 215. Records 109, 111, and 214 provided the LBB examples. Records 118, 124, and 212 provided the RBB sounds. Records 207, 209, and 232 provided the APC examples. There are 450 training set samples and 90 assessment set samples in each of the aforementioned four types of ECG patterns. PVC samples were located by consulting records 106 and 233. In the training set, there are 300 examples of the type of PVC, and there are 60 samples in the assessment set. The ECG trace patterns are shown in Figure 1.

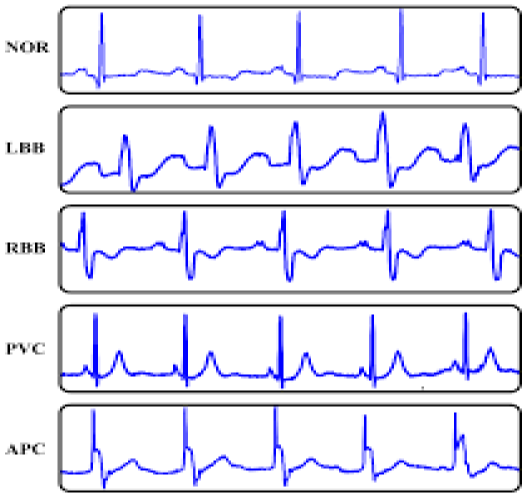

Fig 1. Typical pulse as well as the remainder of the four ECG arrhythmia illnesses' frequencies

III. PROPOSED METHOD

(A)ARRHYTHMIA CLASSIFICATION USING OTHER EXISTING APPROACHES

To compare the suggested 2D-CNN model's performance to Prior investigations used SVM, RNN, RF and K-Nearest Neighbor (K-NN) to classify ECG arrhythmias, and to assess its efficacy in doing so. Because of the different evaluating groups and various kinds of arrhythmia used in these studies, it is unreasonable to explicitly compare precision. However, our proposed CNN model outperformed other previous studies in terms of performance by employing a novel approach to detect ECG arrhythmia disease using a graph based on STFT. Table 2 displays performance contrasts with prior attempts which demonstrates that, in terms of average accuracy, the recommended approach delivered the greatest outcomes.

TABLE II
COMPARISON WITH OTHER EXISTING APPROACHES

Model	*Performance*	*Kinds*	*Evaluating Set*	*Average Accuracy*
CNN	*Proposed*	*5*	*2520*	*99.00%*
FFNN	*Guler et al.[35]*	*4*	*365*	*96.94%*
SVM	*Dutta et al.[38]*	*6*	*40438*	*91.57%*
RNN	*Ubeyli et al.[39]*	*4*	*362*	*98.09%*
RFT	*Kumar etal.[40]*	*3*	*159*	*92.17%*
K-NN	*Park et al.[41]*	*17*	*10972*	*97.00%*

To detect irregular heartbeats and extract features from ECG data, Maya Kallas used Kernel Principal Component Analysis (KPCA) and SVM categorization. Using the wavelet translation and self-regressive simulation wereemployed by Qibin Zhao to capture a characteristic of every ECG interval, and a SVM with a Gaussian kernel was used to categorize various ECG cardiac rhythms. Three separate parts make up the two feature-extraction-pattern classification approaches: data preparation, feature extraction, and ECG signal categorization. Compared to the proposed CNN classifier, feature-extraction processing for feature-extraction-pattern methods is much more difficult.

(B) ARRHYTHMIA CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

Based on the recorded comments provided by two or more cardiologists separately, there are five different classifications of arrhythmia for ECG time domain data. The time domain signals of the ECG, which include those for the five different types of heartbeats (NOR, LBB, RBB, PVC, and APC). Following the Tiny time transform, every ECG signal record is switched into an image of a time-frequency spectrogram, which is then input into the suggested CNN model. Using suggested model generated ECG spectral images, categorization is carried out automatically and intelligentlyby the CNN classifier. Ambulatory samples are included in each ECG signal record, and the initial ECG signal data also contains pulse data from people with cardiovascular diseases.

In this study, a CNN based technique for classifying ECG arrhythmias based on the categorization of five distinct rhythms is proposed. From the time domain raw ECG data, two-dimensional time-frequency spectrograms are produced. However, at this point, there is no more a need for the removal of noise and manual component extraction. Additionally, the improved ECG images that emerge are used to gather training data, which could improve categorization accuracy. Digital wavelength spectral images that have been split are supplied as participation into the convolutional neural network. The model can autonomously reduce appears in readings while retrieving visualizations of significant characteristics from the layer using convolution and putting together. The proposed technique can be applied to ECG data from different ECG gathering devices with different sample rates in order to precisely detect ECG arrhythmia. Preprocessing ECG signal data and CNN classifier phases make up the proposed ECG arrhythmia classification method.

- Data Collection

The collection of data is the first significant stage in the construction of a machine learning model. This can be an essential stage since how well the model operates is going to be affected by the amount of more and improvements in extra information can be obtained. Web scraping and other human actions are examples of data gathering techniques. Arrhythmia Classification Forecasting Machine Learning Algorithms from Kaggle and Other Sources.

- Dataset

The MIT-BIH arrhythmia collection yielded five distinct ECG signal patterns. The pulse data of people with cardiovascular diseases are extracted over the course of an hour from two channel ambulatory samples, which are included in each capture of the initial ECG signal. For each sort of ECG signal, a 10 second segment was selected. The impulses were divided into 2520 segments and then classified as ECG. The relevant information from the arrythmia dataset used is presented in Table 1.

- Data Preprocessing

Image-type data must be provided as input. In order to create time-frequency spectrograms, the time-domain ECG data from five distinct heart illnesses were first transformed using the shortly transform. The immediate frequency of ECG pulse is a unsteady bit of data that varies over time. As a consequence, characterizing the characteristics ofthe changes using only frequency domain data is inadequate. To examine the immediate amplitude as well as frequency of localized waves with time-varying properties, the Time transformer is acreated mathematical tool based on the unique transform.

- ECG Arrhythmia Classifier

As the ECG arrhythmia classifier, CNN is used. LeCun first brought up CNN, which was developed in an effort to recognize scribbled zip numbers. As the CNN model has evolved, correlation between spatially close-by pixels may be restored using a Several filters, including an uncertain filter, which able to derive a number of local features from the image. Convolutional may be a more efficient filter for the geographic localization of ECG images. In order to help CNN, identify ECG patterns, we convert time-domain ECG data into spectrograms in time-frequency representations.

- Analyze and Prediction

To analyze and predict the categorization of arrhythmias using ECG imagery from the MIT- BIH repository which holds large amount of records. Using CNN methods to forecasting arrhythmia disease for the early stages of heart patients.

- ECG Classification Techniques

Electrodes are used in the electrocardiogram (ECG) signal process, which detects minute electrical changes for each heartbeat. This technique is used to examine a variety of aberrant heart functions, involving transpiration and arrhythmias disruption. In this research, the suggested technique uses a classification technique to categorize the ECG records.

Using Naive Bayes, ANN, SVM, and Adaboost classifiers to divide the collection of ECG signals into both usual and unstable ECG signals. According to testing findings, the precision of the SVM, Adaboost, ANN, and Nave Bayes classifiers is 87.5%, 93%, 94, and 99.7%, respectively. When comparison of other classifiers, the precision of a convolutional neural network (CNN) is good.

  - Support Vector Machine

SVM is a technique for supervised learning that increases the accuracy of classification and regression prediction tools. It has a number of uses, including regression, pattern categorization, facial and handwriting analysis, and uses the hypothesis space of a linear function.

SVM's main traits are that it makes it easier to learn complex functions effectively and that it improvesgeneralization by raising the margin. SVM classifiers' initial repetition, known as binary classifiers, produces either a negative or positive result. The test signals are split into normal and pathological ECG signals after the data is educated using a two-class SVM method.

  - Adaboost classifier

Performance is improved by the machine learning meta technique known as Adaptive Boosting Algorithm, or Adaboost. The Adaboost predictor seeks to lower the insufficient classifier's error rate. by introducing a novel predictor. The result of coupling an SVM classifier with an Adaboost classifier in this case serves as a representation of its final classification. But compared to CNN, it is less accurate (93%).

  - Artificial neural network

A network with biological influence known as an ANN can be utilize for a number of tasks, such as pattern detection and classification. Since ANN decision-making is dependent on the characteristics of the input pattern, it is thorough and suitable for the categorization of biological data. Error minimization is the aim of ANN, which makes use of the back propagation method. There is little difference between intended and real production when the weights are determined at random and altered for each period.

The sigmoid function is employed as a trigger rate. Using an ANN classifier, the ECG records is separated into standard and pathological impulses. Sixteen signal datasets are used for classification, and an ANN classifier shows five distinct traits. These are efficiency, confusion, thereceiver and fault histogram working traits as well as train state. However, comparedto CNN, it's precision is lower (94%).

  - Naive Bayes classifier

For categorization tasks, such as text segmentation, a supervised ML technique is the Naive Bayes classifier. It alsobelongs to a group of strategies for learning by repetition, which means it attempts to a simulate the breakdown of the sources within a particular class or group. The models depicting important data groups are extracted using the naive Bayes (NB) classifier data analysis technique. However, when compared to CNN, its precision is lower (99.7%).

V RESULT AND COMPARISON

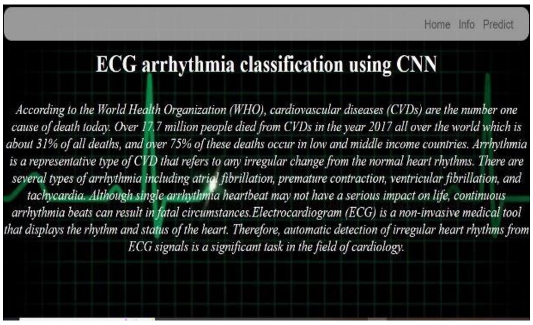

Fig 2. Pages of a website's home page

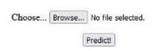

Fig 3. Upload ECG image of the website

The figure 2 indicates the home page of the website. That will redirect to their perspective page which include home that contains the definition of the arrhythmia classification, information and then predict the arrhythmia classification.

The figure 3 indicates the ECG image will be upload that will predict the arrhythmia disease whether the person is affect the arrhythmia or not. The entire arrhythmia procedure takes place on the portable tool, where long-term manual labour is involved.

As a result, categorization outcomes might fall into the positive or negative class groups. The forecast could be right or wrong depending on whether the result falls under the right category or not.

VI CONCLUSION

Throughout this study, a deep learning-based approach for categorizing ECG rhythms was suggested. The MIT-BIH arrhythmia collection yielded five different kinds of ECG patterns. The ECG data was split up into samples that had a 10 second time interval. For ECG classification, 2520 recordings were selected. The recommended technique methods employed the relatively brief transformer to convert time- domain ECG data into two-dimensional ECG spectral patterns with intervals and frequency.

The suggested approach was fed the resulting ECG spectrograms. Using CNN, the ECG arrhythmia was recognized and categorized. The findings demonstrate that a with a mean precision for classification of 99.00, a convolution neural network can categorize cardiac rhythm signals.

A deep learning-based strategy to classifying ECG arrhythmias is suggested. Temporal domain ECG measurements were transformed into time-frequency ECG spectrum using a brief transform. The resulting ECG The suggested strategy included the use of spectrograms. Using CNN, the ECG arrhythmia was determined and described. When compared to manual labor, this is the simple method of identifying the arrhythmia illness.

The results show that ECG data classification was accomplished using convolution neural networks. The correct adaptation of the data by CNN into the optimal number of clusters enables the efficient identification of normal and abnormal instances.

REFERENCES

[1] World Health Organization (2017). Cardiovascular diseases (CVDs).

[2] U. Raghavendra, H. Fujita, A. Gudigar, R. Shetty, K. Nayak, U. Pai, J. Samanth, and U.R. Acharya, Automated technique for coronary artery disease characterization and classification using DD-DTDWT in ultrasound images, Biomedical signal processing andcontrol, 2018, 40: 324-334.

[3] O. Yildirim, A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification, Computers in Biology and Medicine, 2018, 96: 189-202.

[4] Varatharajan R , Manogaran G , Priyan M K. A big data classification approach using LDA with an enhanced SVM method for ECG signals in cloud computing[J].Multimedia Tools and Applications, 2017.

[5] V.H.C. de Albuquerque, T.M. Nunes, D.R. Pereira, E.J.D.S. Luz, D. Menotti,J.P. Papa, J.M.R. Tavares, Robust automated cardiac arrhythmia detection in ECG beat signals,Neural Comput. Appl. 29 (2018) 679–693.

[6] P. Pławiak, Novel methodology of cardiac health recognition based on ECG signalsand evolutionary-neural system, Expert Syst. Appl. 92 (2018) 334–349.

[7] R. Salloum., Kuo C. C. J., ECG-based biometricsusing recurrent neural networks[C]// ICASSP 2017 - 2017IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2017.

[8] A. Mostayed, J. Luo, X. Shu, and et al. Classification of 12-Lead ECG Signals with Bi-directional LSTM Network. 2018.

[9] C. Zhang, G. Wang, J. Zhao, and et al. [ACTAPRESS Biomedical Engineering - Innsbruck, Austria (2/20/2017-2/21/2017)] Biomedical Engineering - Patient- Specific ECG Classification Based on Recurrent Neural Networks and Clustering Technique. 2017.

[10] D. Li, J. Zhang, Q. Zhan, et al. Classification of ECG signals based on 1D convolution neural network[C]//IEEE International Conference on E-health Networking. IEEE, 2017.

[11] T. J. Jun, H. M. Nguyen, D. Kang, and et al. ECG arrhythmia classification using a 2-D convolutional neural network. 2018.

[12] M. Salem, S. Taheri , J. S. Yuan . ECG Arrhythmia Classification Using Transfer Learning from 2- Dimensional Deep CNN Features. 2018.

[13] Rajpurkar, Pranav & Hannun, Awni & Haghpanahi, Masoumeh & Bourn, Codie & Y. Ng, Andrew. Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks, 2017.