**LITERATURE SURVEY**

**INTRODUCTION:**

The electrocardiogram (ECG) is one of the most extensively employed signals used in the diagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart’s rhythmic irregularities, commonly known as arrhythmias. A careful study of ECG signals is crucial for precise diagnoses of patients’ acute and chronic heart conditions. Cardiovascular diseases (CVDs) are the leading cause of human death, with over 17 million people known to lose their lives annually due to CVDs.

According to the World Heart Federation, three-fourths of the total CVD deaths are among the middle and low-income segments of the society. A classiﬁcation model to identify CVDs at their early stage could effectively reduce the mortality rate by providing a timely treatment . One of the common sources of CVDs is cardiac arrhythmia, where heartbeats are known to deviate from their regular beating pattern. A normal heartbeat varies with age, body size, activity, and emotions. In cases where the heartbeat feels too fast or slow, the condition is known as palpitations. An arrhythmia does not necessarily mean that the heart is beating too fast or slow, it indicates that the heart is following an irregular beating pattern. It could mean that the heart is beating too fast—tachycardia (more than 100 beats per minute (bpm)), or slow—bradycardia (less than 60 bpm), skipping a beat, or in extreme cases, cardiac arrest. Some other common types of abnormal heart rhythms include atrial ﬁbrillation, atrial ﬂutter, and ventricular ﬁbrillation. These deviations could be classiﬁed into various subclasses and represent different types of cardiac arrhythmia. An accurate classiﬁcation of these types could help in diagnosing and treatment of heart disease patients. Arrhythmia could either mean a slow or fast beating of heart, or patterns that are not attributed to a normal heartbeat. An automated detection of such patterns is of great signiﬁcance in clinical practice. There are certain known characteristics of cardiac arrhythmia, where the detection requires expert clinical knowledge. The electrocardiogram (ECG) recordings are widely used for diagnosing and predicting cardiac arrhythmia for diagnosing heart diseases. Towards this end, clinical experts might need to look at ECG recordings over a longer period of time for detecting cardiac arrhythmia. The ECG is a one-dimensional(1-D) signal representing a time series, which can be analyzed using machine learning techniques for automated detection of certain abnormalities. Recently, deep learning techniques have been developed, which provide signiﬁcant performance in radiological image analysis.

**EXISTING METHODS:**

Convolutional neural networks (CNNs) have recently been shown to work for multi-dimensional (1-D, 2-D, and in certain cases, 3-D) inputs but were initially developed for problems dealing with images represented as two-dimensional inputs. For time series data, 1-D CNNs are proposed but are less versatile when compared to 2-D CNNs. Hence, representing the time series data in a 2-D format could beneﬁt certain machine learning tasks . Hence, for ECG signals, a 2-D transformation has to be applied to make the time series suitable for deep learning methods that require 2-D images as input. The short-time Fourier transform (STFT) can convert a 1-D signal into a 2-D spectrogram and encapsulate the time

and frequency information within a single matrix. The 2-D spectrogram is similar to hyper-spectral and multi-spectral images (MSI), which have diverse applications in remote sensing and clinical diagnosis, including spectral un-mixing, ground cover classiﬁcation and matching, mineral exploration, medical image classiﬁcation, change detection, synthetic material identiﬁcation, target detection, activity recognition, and surveillance . The 2-D matrix of spectrogram coefﬁcients could be useful for extracting robust features for representation of a cardiac ECG signal.

This representation could allow the application of CNN architectures (designed to operate on 2-D inputs) for development of automated systems related to CVDs.1.1. Related Works. The ECG signal detects abnormal conditions and malfunctions by recording the potential bio-electric variation of the human heart. Accurately detecting the clinical condition presented by an ECG signal is a challenging task. Therefore, cardiologists need to accurately predict and identify the right kind of abnormal heartbeat ECG wave before recommending a particular treatment. This might require observing and analyzing ECG recordings that might continue for hours (patients in critical care). To overcome this challenge for the visual and physical explanation of the ECG signal, computer-aided diagnostic systems have been developed to automatically identify such signals automatically. Most of the research in this ﬁeld has been conducted by incorporating different approaches of machine learning (ML) techniques for the efﬁcient identiﬁcation and accurate examination of ECG signals. ECG signal classiﬁcation based on different approaches has been presented in the literature including frequency analysis , artiﬁcial neural networks (ANNs) [22],heuristic-based methods, statistical methods , support vector machines (SVMs) , wavelet transform , ﬁlter banks hidden Markov models , and mixture-of-expert methods. An artiﬁcial neural network based method obtained an average accuracy of 90.6% for the classiﬁcation of ECG wave into six classes. Meanwhile, a feed-forward neural network was used as a classiﬁer for the detection of four types of arrhythmia classes and achieved an average accuracy of 96.95% .

**DEEP LEARNING:**

Machine learning is a subset of artiﬁcial intelligence used with high-end diagnostic tools for the prediction and diagnosis of different types of illnesses. Deep learning, as a subset of ML, has many applications in the prediction and prevention of fatal sicknesses, particularly CVDs. Different techniques of deep learning used for the analysis of bioinformatics signals have been presented in . A recurrent neural network (RNN) was used for feature extraction and achieved an average accuracy of 98.06% for detecting four types of arrhythmia. For the classiﬁcation and extraction of features from a 1-D ECG signal, a 1-D convolutional neural network model was proposed and yielded a classiﬁcation accuracy of 96.72%. Another deeper 1-D CNN model was proposed for the classiﬁcation of the ECG dataset and obtained an average accuracy of 97.03%. In both instances, a large ECG dataset was used, but the ECG signals were represented as a 1-D time series. A nine-layer2-D CNN model was applied for an automatic classiﬁcation of ﬁve different heartbeat arrhythmia types achieving an accuracy of 94.03%. Deep Learning (DL) has recently become a topic of study in different applications including healthcare, in which timely detection of anomalies on Electrocardiogram (ECG) can play a vital role in patient monitoring.

**PROPOSED SOLUTIONS:**

A previously proposed paper presents a comprehensive review study on the recent DL methods applied to the ECG signal for the classification purposes. This study considers various types of the DL methods such as Convolutional Neural Network (CNN), Deep Belief Network (DBN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). From the 75 studies reported within 2017 and 2018, CNN is dominantly observed as the suitable technique for feature extraction, seen in 52% of the studies. DL methods showed high accuracy in correct classification of Atrial Fibrillation (AF) (100%), Supra ventricular Ectopic Beats (SVEB) (99.8%), and Ventricular Ectopic Beats (VEB) (99.7%) using the GRU/LSTM, CNN, and LSTM, respectively. High-risk patients of cardiovascular disease can be provided with computerized electrocardiogram (ECG) devices to detect Arrhythmia. These require long segments of quality ECG which however can lead to missing the episode. To overcome this, it has been proposed a deep-learning approach, where the scalogram obtained by continuous wavelet transform (CWT) is classified by the network based on the signature corresponding to arrhythmia. The CWT of the recordings is obtained and used to train the 2D convolutional neural network (CNN) for automatic arrhythmia detection. Here, the proposed model is trained and tested to identify five types of heartbeats such as normal, left bundle branch block, right bundle branch block, atrial premature, and premature ventricular contraction. The model shows an average sensitivity, specificity, and accuracy to be 98.87%, 99.85%, and 99.65%, respectively. The result shows that the proposed model can detect arrhythmia effectively from short segments of ECG and has the potential for being used for personalised and digital healthcare. The early diagnosis of cardiovascular infection is focused on exploration and distinction signs of arrhythmia. Throughout this analysis it is proposed the interaction between CNN-LSTM and FCL to improve the preparedness influence, limiting the effects on the model training of an enormous amount of basic specific ECG beat information. The proposed architecture utilizes CNNs to decrease each spectral variation in the input feature but instead moves it on to LSTM layers while providing outputs to DNN layers, which have a more effective feature representation. The findings indicate that CNN-LSTM and FCL have obtained 99.33%, 96.06%, 94.36%, and 92.65%, individually, with the results being accuracy, F1 score, precision, and recall. The adequacy and intensity of the proposed architecture were seen by the MIT-BIH arrhythmic test results. The methodology proposed could be used to help cardiologists in diagnosing ECGs with a better level of accuracy and impartiality in telemedicine scenarios. In future examinations, various kinds and specific beats will be included. In addition, to analyze the appearance of the CNN LSTM using the FCL pattern, it is intend also to introduce specific rates of noise to ECG signals. The ECG image from ECG signal is processed by some image processing techniques.

To optimize the identification and categorization process, this research presents a hybrid deep learning-based technique. This paper contributes in two ways. Automating noise reduction and extraction of features, 1D ECG data are first converted into 2D pictures. Then, based on experimental evidence, a hybrid model called CNNLSTM is presented, which combines CNN and LSTM models. A comprehensive research has been conducted using the broadly used MIT\_BIH arrhythmia dataset to assess the efficacy of the proposed CNN-LSTM technique. The results reveal that the proposed method has a 99.10 percent accuracy rate. Furthermore, the proposed model has an average sensitivity of 98.35 percent and a specificity of 98.38 percent. These outcomes are superior to those produced using other procedures, and they will significantly reduce the amount of involvement necessary by physicians. Arrhythmia categorization is the most important topic in medicine. The heart rate irregularity is known as an arrhythmia. This study developed an approach for computerized cardiac arrhythmia monitoring using the CNN-LSTM model. This technique employs convolutional neural network for feature engineering and LSTM for categorization, and it uses the CWT to transform 1D ECG signals into 2D ECG image plots, making them a suitable raw input for this network. Investigations on three ECG cross data bases showed that they can outperform other classification methods when used correctly.The MIT–BIH arrhythmia database information was divided into pathologic and normal categories depending on the ECG beat types shown in it. The confusion matrix for the testing dataset revealed that “regular sinus rhythm” had 99 percent validation accuracy, “cardiac arrhythmias” had 98.7% validation accuracy, and “congestive heart attacks” had 99 percent validation accuracy. Furthermore, ARR has 0.98 percent sensitivity and 0.98 percent specificity, while CHF has 0.96 percent sensitivity and 0.99 percent specificity, and NSR has 0.97 percent sensitivity and 0.99 percent specificity. Our methodology beats earlier methods in terms of overall efficiency. Furthermore, CWT&#39;s large computational load is a negative. Although it would considerably reduce the amount of intervention required by physicians, it could not ever achieve a comprehensive inter subject state. It would be an excellent next research topic. To address these challenges, a reliable arrhythmia classification system is required.

In another study, it proposes a two-dimensional (2-D) convolutional neural network (CNN) model for the classiﬁcation of ECG signals into eight classes; namely, normal beat, premature ventricular contraction beat, paced beat, right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat, ventricular ﬂutter wave beat, and ventricular escape beat. The one-dimensional ECG time series signals are transformed into 2-D spectrograms through short-time Fourier transform. The 2-D CNN model consisting of four convolutional layers and four pooling layers is designed for extracting robust features from the input spectrograms. The proposed methodology is evaluated on a publicly available MIT-BIH arrhythmia dataset. They achieved a state-of-the art average classiﬁcation accuracy of 99.11%, which is better than those of recently reported results in classifying similar types of arrhythmias. The performance is signiﬁcant in other indices as well, including sensitivity and speciﬁcity, which indicates the success of the proposed method to some extent. Although there are many previously proposed models, the accuracy rate still needs an improvement. A solution for this problem needs to be devised ignorer to accurately find the type and extent of the abnormality.

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