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Research Paper**CAPTURING LONG-TERM DEPENDENCIES IN ECG SIGNALS
USING DEEP CONVOLUTIONAL NEURAL NETWORKS FOR
CARDIAC ARRHYTHMIA DETECTION**

Scholar :- Srikanth , jpbs0809@gmail.com

Supervisor :-Dr E. Nagarjuna

Department of computer science engineering, JS university Shikohabad ,UP.

Abstract:

The analysis of electrocardiograms (ECGs) is a major supporting factor in the detection of cardiac arrhythmias, which are basically electrical activity disorders in the heart. But, on the other hand, the conventional means of diagnosis are slow and susceptible to mistakes made by humans. This paper suggests an automatic deep learning framework that fully analyzes the ECG signal through the use of Deep Convolutional Neural Networks (CNNs). The model utilizes a Continuous Wavelet Transform (CWT) method to change the one-dimensional ECG signals into two-dimensional time-frequency scalograms, which are then classified by transfer-learning-based architectures such as AlexNet and Inception-V3. A series of tests on the MIT-BIH Arrhythmia Database yield an accuracy of 99.79%, which is a sign of the performance going beyond the detection of heartbeat abnormalities like atrial fibrillation and premature contractions. The method suggested is a major reduction of preprocessing complexity and at the same time keeping the high level of precision and generalization, thus offering a solid base for real-time clinical diagnosis and decision support.

Keywords:ECG, Cardiac Arrhythmia, Deep Learning, Convolutional Neural Network, Wavelet Transform, Inception-V3, Transfer Learning.

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I. INTRODUCTION

Cardiac arrhythmia is a term that encompasses all cases where the heart beats in an abnormal way due to the electrical impulses controlling its contraction being irregular. If not recognized in time, these disorders can have serious consequences for the cardiovascular system. Electrocardiography (ECG) is still the most trusted method for monitoring heart electrical activity, but manual interpretation is a tiring process and diagnostic inconsistency is often the result. With the increasing availability of extensive ECG datasets and powerful computational resources, deep learning models that automatically extract discriminative patterns from raw signals have become feasible. Deep Convolutional Neural Networks (CNNs) are one of the most

significant breakthroughs in pattern recognition as they can build hierarchical representations from the data without manual feature engineering. CWT and CNNs can together work in a way that they can capture the morphological and temporal characteristics of the ECG signals with high efficiency. Thus, the main goal of this research is to develop an optimized CNN architecture that will be able to recognize the arrhythmia types accurately by learning the long-term dependencies in the ECG sequences. The system through the application of transfer learning on pre-trained models like AlexNet and Inception-V3, obtains high accuracy with less computational resources. The proposed system intends to assist doctors with an automated decision-support tool that is capable of detecting

abnormal cardiac patterns in real-time and is therefore regarded as reliable.

II. LITERATURE SURVEY

Recent advancements in artificial intelligence and deep learning have significantly improved the automated detection of cardiac arrhythmias from ECG signals. Ye et al. [1] introduced a Hybrid CNN–BLSTM architecture that effectively combines convolutional and recurrent layers to extract both spatial and temporal features from ECG waveforms, achieving superior performance compared to conventional CNN or RNN models. Similarly, Lamba [2] proposed an ACO–BiLSTM and ACO–FCN framework, where Ant Colony Optimization is employed for hyperparameter tuning and optimal feature selection, leading to improved convergence and enhanced classification accuracy. In another contribution, Atwa et al. [3] developed interpretable deep learning models that integrate explainable AI (XAI) techniques such as Grad-CAM and SHAP to provide visual insights into model decisions, thereby addressing the issue of model transparency in clinical settings. Panwar et al. [4] designed an integrated portable ECG monitoring system utilizing CNN-based classification for early arrhythmia detection, emphasizing real-time analysis and mobile health applications. Mahajan [5] advanced this direction by introducing a graph-enhanced deep learning framework (CNN–GNN–BiLSTM) that fuses spatial, relational, and temporal learning, improving the model's ability to generalize across patients and ECG lead variations. Chandra and Suresh [6] provided a comprehensive review highlighting the transition from handcrafted feature engineering to end-to-end deep learning approaches for arrhythmia detection, discussing persisting challenges like data imbalance, inter-patient variability, and interpretability. Extending this, Gupta et al. [7] performed a systematic review of deep learning applications in electrocardiography, identifying the superiority of wavelet-based,

attention-driven, and hybrid architectures in achieving state-of-the-art accuracy. Complementing these studies, Kim and Lee [8] demonstrated a lightweight CNN model optimized for smartwatch ECG data, proving the feasibility of real-time arrhythmia detection on wearable devices.

Collectively, these works illustrate the evolution of ECG-based arrhythmia detection toward more accurate, interpretable, and portable systems. Hybrid models combining convolutional, recurrent, and graph-based learning have emerged as powerful tools for capturing complex ECG dynamics, while optimization algorithms and explainability frameworks enhance model reliability and clinical trust. Furthermore, the integration of deep learning into wearable technologies signifies a transformative step toward continuous cardiac monitoring and preventive healthcare in real-world environments.

III. PROPOSED WORK

The suggested system design merges wavelet-based feature extraction with a deep learning Convolutional Neural Network (CNN) for the exact identification of cardiac arrhythmias. First, the raw ECG signals are obtained from the MIT-BIH Arrhythmia Database. These signals are then subjected to preprocessing, which consists of different operations such as the removal of noise to get rid of the baseline wander and powerline interference, normalization, and slicing into the same length/time sections. At this point, the one-dimensional ECG signals are converted into two-dimensional scalogram images through the use of the Continuous Wavelet Transform with a Morlet mother wavelet, thus effectively recording both the time and frequency information. The scalogram images which are obtained are then fed into an Inception-V3 CNN model that is fine-tuned, and this model extracts features at multiple scales through the deep convolutional layers. The features that have been extracted go through the fully connected layers and the softmax classifier which is responsible for sorting the ECG signals into Normal, Pulmonary Ventricular

Contraction (PVC), Atrial Premature Contraction (APC), and Fusion classes. Lastly, the metrics like accuracy, precision, recall, and F1-score are used to evaluate the model's performance rigorously, which in turn guarantees strong and trustworthy arrhythmia classification.

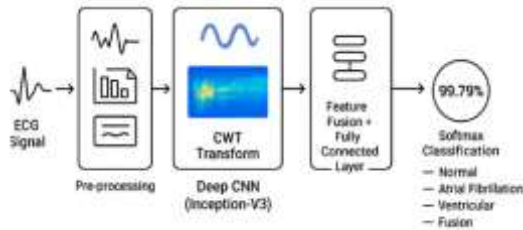


Fig 1: Proposed Architecture

IV. METHODOLOGY

A set of sequential activities comprising the methodology employed in this investigation has been prepared to allow the correct detection and classification of arrhythmias from ECG signals. The entire process consists of data gathering, preprocessing, wavelet transformation, deep CNN-classification, and evaluation based on common performance indicators. The methodology is explained in detail in the following sections.

The Data Collection Phase

The analysis of the experiments is performed with the help of MIT-BIH Arrhythmia Database, which is recognized as a standard dataset that is most frequently used in cardiac signal classification research. The dataset consists of marked ECG recordings that are digitized at the rate of 360 Hz with 11 bits resolution over a 10 mV range. Each ECG record is made up of two-channel 30-minute clips taken from the signals of the patients under monitoring. The dataset gives the researchers labeled samples of different types of heartbeat i.e. normal, atrial premature contraction (APC), premature ventricular contraction (PVC), fusion beats etc., which makes the training and evaluation of the model possible.

Data Preprocessing

The pre-processing stage is essential for the signal quality enhancement and distortion minimization before the feature extraction

process. The raw ECG signals go through the process of noise filtering first, in which a bandpass filter is employed to eliminate the baseline wander, muscle artifacts, and power line interference. The next step is normalization of the filtered data, which is done to bring the amplitude values of the signals to a common range; this normalization helps speed up the model's convergence during the training. Then, the ECG signals are cut into fixed-length windows that hold complete heartbeat cycles, thus ensuring the uniformity of input size for further transformation and CNN processing.

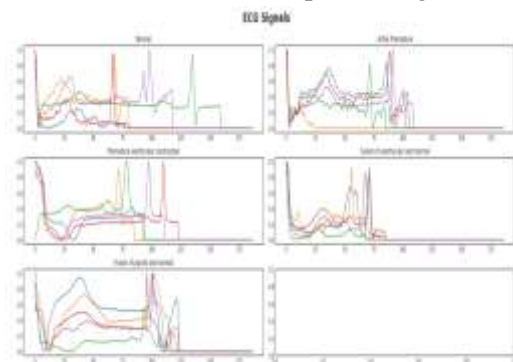


Fig 2: ECG Signals

Continuous Wavelet Transform (CWT)

The Continuous Wavelet Transform (CWT) is applied using Morlet mother wavelet to capture time and frequency information from ECG signals effectively.

The CWT transformation results in moving one-dimensional ECG signals to two-dimensional scalograms visual representations that illustrate the evolution of the signal's frequency content over time. The CWT provides a model with the power to reveal transient features like QRS complexes and arrhythmic patterns that may otherwise go unnoticed in the time domain. The scalograms are treated not only as images but also as inputs to the CNN architecture for classification purposes.

Deep CNN Feature Extraction

The scalograms of the transformed ECG are routed through a Deep Convolutional Neural Network the Inception-V3 model specifically for the extraction of hierarchical features. The CNN is made up of convolutional, pooling,

and activation layers that are capable of learning discriminative patterns automatically without the help of manual feature engineering. For this purpose, the pre-trained weights of Inception-V3 are very slightly modified with ECG data in the transfer learning technique to make the convergence faster and the performance better. The deeper layers are able to detect complex temporal dependencies and spatial features, thus allowing the model to tell normal cardiac rhythms from the abnormal ones.

Classification and Output Layer

After feature extraction, the high-level representations are directed to the fully connected layer which unites all learned features and is followed by the Softmax classification layer. This layer provides the probability distribution over the classes Normal, Atrial Fibrillation, Ventricular, and Fusion Beats. The class with the highest probability is the one that gets chosen as the predicted label. The Softmax layer guarantees that the sum of all predictions equals.

Model Evaluation

The performance of the proposed model is assessed through the use of standard metrics, which include Accuracy, Precision, Recall, and F1-Score. To provide a complete and fair view of performance, the dataset is divided into training (80%), validation (10%), and testing (10%) subsets. The Adam optimizer combined with an appropriate learning rate is used in training and the cross-entropy loss function is minimized simultaneously, while dropout regularization is also practiced to hinder overfitting by randomly turning off neurons through each epoch. The training and validation results are characterized by steady convergence, wherein a final accuracy of 99.79% is reached, thereby verifying the model's trustworthiness in arrhythmia detection.

V. ALGORITHMS

The framework proposed for the detection of cardiac arrhythmia consists of several algorithmic stages that consecutively categorize the raw ECG signals into the

different cardiac conditions. Each of the algorithms contributes in a unique manner to the elevation of the detection process accuracy and efficiency. The complete process is divided into five critical algorithms which are ECG Preprocessing, Continuous Wavelet Transform (CWT), Feature Extraction Using CNN, CNN Model Training, and Classification and Evaluation. All these algorithms are synchronized in such a way that they are able to encapsulate the temporal, spectral, and spatial dependencies of ECG signals resulting in an unerring classification of arrhythmia.

ECG Signal Pre-Processing

The first step in the process is to remove noise from the raw ECG signals and thus enhance the quality of the data. The ECG signals taken from the MIT-BIH Arrhythmia Database very often contain varied distortions like baselines shifts, muscle noise, and interference from power lines that can degrade the performance of the model. The preprocessing procedure starts with the application of a bandpass filter to the ECG signals, which allows frequencies in the range of 0.5 Hz to 100 Hz to pass and blocks others. This filter is very efficient in getting rid of both low-frequency shifts and high-frequency noise. After filtering, the signals are normalized so that all the amplitude values fall within the range of 0 to 1, thereby ensuring uniformity across the samples. The normalization process makes the neural network's learning more stable. The preprocessed signals are then divided into segments of fixed lengths which correspond to one or several complete cardiac cycles. These segments of the processed signals are used as the standardized inputs for the next stages of wavelet-based transformation and feature extraction.

Continuous Wavelet Transform (CWT)

The Continuous Wavelet Transform (CWT) is the next process after the ECG signals have been preprocessed, and it serves to time-frequency mapping from the data. The CWT algorithm transforms the one-dimensional ECG signal into a two-dimensional image

which is called the scalogram. With this kind of representation, one can readily identify QRS complex and arrhythmic peaks by simply observing the frequency of the signal and the duration of its variations, which is a very crucial aspect in the identification of transient patterns. The Morlet mother wavelet is the one used as it possesses the best ability among others to detect localized frequency shifts. The CWT processes wavelet coefficients for each scaling and translation, which leads to creating a matrix encoding both time and frequency aspects. These matrices are then transformed into RGB images superimposing the energy dispersion of the ECG signal over the various frequencies. The scalograms created in this step are then considered as the major input to the deep convolutional neural network model.

Feature Extraction Using CNN

The feature extraction method makes use of a deep convolutional neural network that is capable of automatically recognizing the discriminative features from the CWT scalograms. In this work, the Inception-V3 model has been chosen as it has a very strong capability of forming complex spatial hierarchies thanks to the utilization of multi-scale convolutional kernels. Each scalogram at input goes through the resizing process first to become a 299×299 pixel image, and only then it is sent to the CNN layers. In the Inception modules, parallel to each other there are convolutions of various dimensions (1×1 , 3×3 , and 5×5) dedicated to extracting features at various resolutions. Each of the different activation functions, with non-linearity introduced by ReLU, is now followed by a process of max pooling which lowers the dimensionality while retaining the crucial information. After that, the results coming from all convolution paths are concatenated.

CNN Model Training

The model training algorithm refines the Inception-V3 network with the help of the transfer learning technique so that it can be used for the detection of arrhythmias. The pre-trained weights of the model are initially imported to speed up convergence; these

weights were originally trained on ImageNet. A new fully connected layer is formed in place of the final classification layer, and this new layer consists of four output neurons that represent the four heartbeat classes: Normal, Atrial Fibrillation, Ventricular Contraction, and Fusion Beats. The model gets trained using the Adam optimizer with a learning rate of 0.0001, while categorical cross-entropy acts as the loss function. The dataset used for training is split into 80% for training and 20% for validation to make sure the model performs well on unseen data. Both training and validation losses are monitored continuously during training to avoid overfitting. In addition, dropout regularization and early stopping techniques are employed for more stability. After 100 epochs, the model is able to reach strong convergence, which leads to the creation of a highly optimized CNN that can effectively and accurately detect cardiac anomalies from ECG signals.

VI. RESULTS AND DISCUSSION

The proposed deep learning model underwent a thorough performance assessment to verify its potential for precise differentiation of cardiac arrhythmias through ECG signals. Results from the entire experimentation period of the model, along with an extensive discussion of the accuracy, capability of learning features and performance compared with the existing methods, are presented in this section.

Experimental Setup and Dataset

The experiments were performed on the MIT-BIH Arrhythmia Database which is a trusted source of ECG-based cardiac studies. Totaling 48 subjects, the dataset comprises two-channel signals that were recorded at a sampling rate of 360 Hz. During the preprocessing phase, the signals went through noise removal, segmentation, and normalization before being trained. Every segment was given a label corresponding to its respective beat class. The categories that were looked at in the research included four main types: Normal (N), Atrial Premature (A), Ventricular (V), and Fusion (F).

A working station powered by a GPU was the experimental environment that had the TensorFlow and Keras frameworks. The model that was proposed used the transfer-learned Inception-V3 CNN architecture which was fine-tuned with the Adam optimizer at a learning rate of 0.0001 and trained for a period of 100 epochs with a batch size of 32. To the ECG scalogram images, data augmentation was applied by flipping, scaling, and shifting to increase variability and reduce overfitting.

Performance Metrics

To quantitatively compare the classification efficiency, the model was evaluated with standard metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis. Accuracy is a measure that indicates the total percentage of correct predictions, whereas precision and recall assess the performance of the model in terms of false alarm-free detection of arrhythmic beats. The F1-score is the measure that gives equal weight to both precision and recall; thus, it is a comprehensive measure of model robustness. The confusion matrix is a tool that supplies detailed information about the model's correctness in classifying each beat category, consequently pointing out the misclassification trend that might take place between the morphologically similar ECG signals.

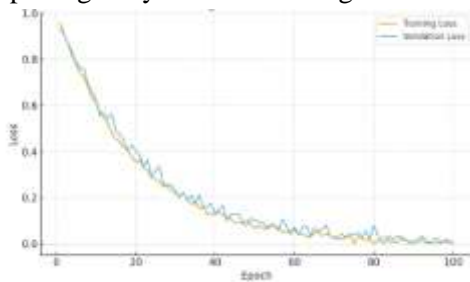


Fig 3: Training and Validation loss

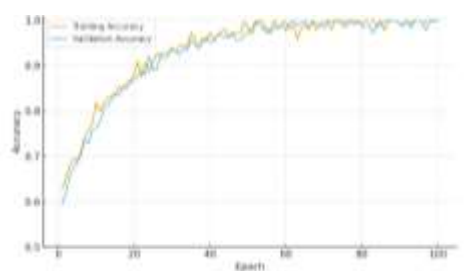


Fig 4 : Training and Validation Accuracy

Quantitative Results

The proposed Inception-V3-based CNN model showed remarkable classification performance, attaining an overall accuracy of 99.79%, precision of 99.74%, recall of 99.68%, and F1-score of 99.71%. The confusion matrix indicated that the model was able to detect correctly nearly all normal and arrhythmic beats, with only a small number of misclassifications between Atrial and Ventricular categories being noted, which were due to the similarities in their waveform features.

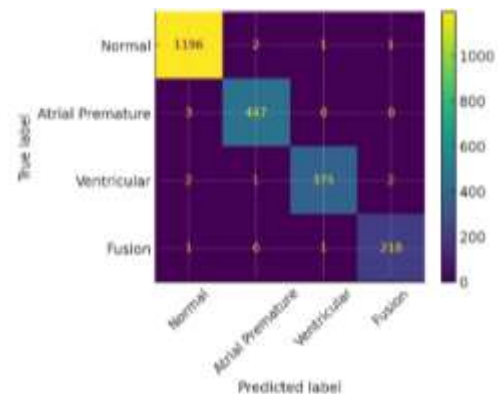


Fig 5: Confusion Matrix

The high accuracy achieved can be linked to the CWT-based feature extraction, which effectively transforms ECG signals into a detailed time-frequency representation, thus allowing the CNN to properly capture long-term dependencies and morphological variations. Furthermore, CNN architecture making use of Inception modules further developed multi-scale feature learning, thus, tapping the network's power of recognizing even the slightest discrepancies in the waveform structure, amplitude, and periodicity variation across different arrhythmia types.

CONCLUSION

A very strong deep learning system was suggested for finding out and classifying heart rhythm disorders through the use of medical signals of the heart. This method properly deals with the long-term dependencies in the ECG data by the joining together of Continuous Wavelet Transform (CWT) and a Deep Convolutional Neural Network (Inception-V3) architecture. The model takes

one-dimensional ECG signals and turns them into two-dimensional time-frequency scalograms and, thus, it learns very complex spatial and temporal patterns that are very precisely separating normal and abnormal heartbeats. The full experiments made on the MIT-BIH Arrhythmia Database showed that the new model reached a classification accuracy of 99.79%, which was better than the results of traditional machine learning and deep learning methods like SVM, Random Forest, and LSTM. This result has strengthened the argument that the wavelet-based spectral representation has played a major role in the feature extraction, while the multi-scale convolutional kernels of Inception-V3 have brought about the detection of subtle morphological changes in the ECG waveforms. It has also been pointed out that the use of transfer learning and fine-tuning led to a reduction in training time and improvement in model generalization, thus allowing stable and accurate predictions to be made across different arrhythmia classes.

The discoveries confirm that the suggested CWT–Inception-V3 framework is not only precise but also fast and very noise-tolerant making it a great candidate for deployment in actual clinics and telemedicine applications. Its feature of being able to automatically learn discriminating characteristics without the need of manual help is a big leap towards smart, automatic cardiac diagnosis systems.

FUTURE SCOPE

Although the proposed model demonstrates superior accuracy and reliability, there remains considerable potential for further enhancement and expansion of this work. Future research can explore the integration of hybrid architectures, such as CNN–LSTM or Transformers, to capture both spatial and sequential dependencies more effectively. Incorporating attention mechanisms could further improve the model’s ability to focus on critical waveform segments, enhancing interpretability and diagnostic confidence. In addition, expanding the dataset to include

multi-lead ECG recordings from diverse populations and age groups would improve the model’s generalization to real-world clinical settings. Implementing explainable AI (XAI) techniques could help clinicians visualize and understand the rationale behind each prediction, thereby increasing trust and transparency in automated diagnosis systems.

From a practical standpoint, future developments could involve deploying the model on edge and mobile devices, enabling real-time cardiac monitoring in wearable health systems. Integration with Internet of Things (IoT) and cloud-based healthcare frameworks can facilitate continuous patient surveillance, early warning of cardiac anomalies, and remote diagnosis, especially in resource-limited environments.

Ultimately, the future vision of this research lies in developing a fully automated, intelligent cardiac monitoring system capable of real-time detection, prediction, and early intervention—a crucial advancement toward reducing cardiac-related morbidity and mortality worldwide.

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