Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2025 SCPE. Volume 26, Issues 1, pp. 371–387, DOI 10.12694/scpe.v26i1.3638

A NOVEL DEEP LEARNING-BASED CLASSIFICATION APPROACH FOR THE DETECTION OF HEART ARRHYTHMIAS FROM THE ELECTROCARDIOGRAPHY SIGNAL

ABDUL RAZZAK KHAN QURESHI[*], GOVINDA PATIL[†], RUBY BHATT [‡], CHHAYA MOGHE [§], HEMANT PAL [¶], AND CHANDRESH TATAWAT[‖]

Abstract. Cardiovascular disease causes more deaths than any other cause in the globe. The present method of illness identification involves electrocardiogram (ECG) analysis, a medical monitoring gadget that captures heart activity. Regrettably, a great deal of medical resources is required to locate specialists in ECG data. Consequently, ML feature detection in ECG is rapidly gaining popularity. Human intervention is required for "feature recognition, complex models, and lengthy training timeframes"—limitations that are inherent to these traditional approaches. Using the "MIT-BIH Arrhythmia" database, this study presents five distinct categories of heartbeats and the efficient and effective deep-learning (DL) classification algorithms that go along with them. The five types of pulse features are classified experimentally using the wavelet self-adaptive threshold denoising method. Models such as AlexNet and CNN are employed in this dataset. For model evaluation use some performance metrics, like recall, accuracy, precision, and f1-score. The suggested Alex Net model achieves an overall classification accuracy of 99.68%, while the recommended CNN model achieves an accuracy of 99.89%. The end findings demonstrate that the suggested models outperform the current model on several performance criteria and are more efficient overall. With its accurate categorization, important medical resources are better preserved, which has a positive effect on the practice of medicine.

Key words: ECG, Detection, Heart Arrhythmias, deep learning, heart disease.

1. Introduction. The body is the motor that transmits blood to a system of interconnected arteries. The heart is always in motion, pumping forth oxygen and nutrients and expelling waste products at a rate of 100,000 beats each day. An electrocardiogram (ECG) records the electrical activities that the heart makes when it beats. The top ten global health problems for 2019 have been unveiled by the World Health Organization (WHO) recently. Coronary disease is an infectious disease that is frequent and may be easily prevented. Early screening therapies are crucial because to the difficulty of restoration. A crucial instrument for continually documenting the heart's electrical function across time is an ECG. More than 300 million clinical electrocardiogram recordings are stored in clinics around the globe [4]. An electrocardiogram (ECG) is the gold standard for regular evaluations since it is needed, beneficial, and cautious. Common applications include clinical screening for various cardiovascular infections, identifying myocardial architecture, simulating the heart's anatomy, and providing doctors with crucial reference data; and making a determination on arrhythmia.

Certain illnesses affecting the circulatory system can have an immediate impact on blood pressure, and cardiac rhythm problems are one of their underlying causes. Paralysis, stroke, or death can result from these erratic fluctuations in blood pressure. There are two broad categories that may be used to describe rhythm abnormalities that are associated with heart rate. Blood pressure and heart rate are both affected. Rapid heartbeats, over 100 beats per minute, are known as tachycardia. Barycardia describes rhythm problems in which the heart rate is below 60 beats per minute [18]. Arrhythmias of the heart often refer to irregularities or disruptions in the heart's electrical activity. Arrhythmia, or irregular heart rate and rhythm, is a symptom of certain diseases. The heart's location in the circulatory system makes the time between heartbeats at blood's

[*]Department of Computer Science, Medi-Caps University Indore, Madhya Pradesh, India. (dr.arqureshi786@gmail.com).
[†]Department of Computer Science, Medi-Caps University Indore, Madhya Pradesh, India. (patil.govinda1976@gmail.com)
[‡]Department of Computer Science, Medi-Caps University Indore, Madhya Pradesh, India.(profrubybhatt15@gmail.com)
[§]Department of Computer Application, Medi-Caps University Indore, Madhya Pradesh, India.(ckapse06@gmail.com)
[¶]Department of Computer Science, Medi-Caps University Indore, Madhya Pradesh, India.(hemantpal.scs@gmail.com)
[‖]Department of Computer Science and Engineering, Medi-Caps University Indore, Madhya Pradesh, India. (tatawatchandresh99@gmail.com)

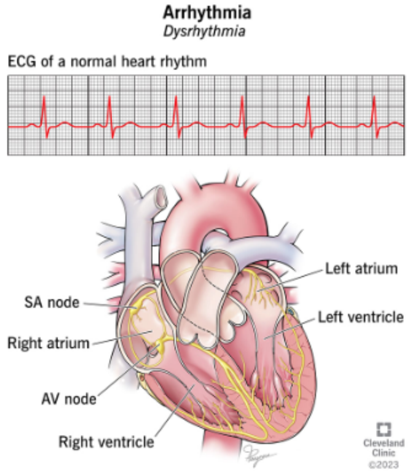

Fig. 1.1: Heart Arrhythmia

entry and departure from the heart extremely important for the identification and management of rhythm problems. In plain terms, in the absence of a rhythm issue, the time it takes for the heart to contract and relax should be relatively close. Arrhythmia symptoms include irregular heartbeats or times that are either too long or too short according to predetermined standards [2]. In electrocardiogram (ECG) readings, these arrhythmias show up as anomalies or distortions in the waveform that occur naturally. There are three main categories of causes for rhythm disorders: mental health issues, stress (both physical and emotional), and cardiac issues. In light of these considerations, the identification and categorization of rhythm problems are critical steps in the disease's management.

DL has proven especially beneficial in the fields of medical image analysis, among other applications of artificial intelligence [5]. For the purpose to study ECG signals and the identification of arrhythmias, neural networks would deem themselves excellent due to the ability to learn autonomously complex patterns and other characteristics in raw data. DL methods can process not only numerous temporal and spatial correlations inside the ECG data but also do highly accurate classification of different types of arrhythmia. In the area of arrhythmia detections, the benefits of blending DL algorithms with ECG readings are numerous. For instance, a deep learning and neural network-based model capable of accurately capturing the pattern-based and character-specific characteristics of arrhythmias that are often unpredictable and complex could be utilized for managing ECG (electrocardiogram) related data. Given these purposes, the machine learning models may become trained through the use of very extensive datasets which contain a large number of arrhythmia instances that differ from one another.

1.1. Research motivation and contribution. The motivation for developing a more stable ResNet-18 model for ECG heartbeat classification is to enhance the reliability and accuracy of cardiovascular disease detection. Maintaining a healthy heart is essential to one's well-being as a whole. Among the leading causes of death worldwide are diseases affecting the cardiovascular system, including heart attacks and strokes. Patient outcomes and healthcare system burden can be significantly improved with early detection and treatment of these disorders.

This study main aim of this study is to compare various techniques and methods of heart Arrhythmia detection using DL techniques. This study contributes to the advancement of cardiovascular disease research by proposing a novel approach to classify arrhythmias based on their morphological and rhythmic patterns. Through the utilization of ECG tests and advanced deep learning models like CNN or AlexNet, the system demonstrates superior performance in identifying irregular heartbeats, as evidenced by improved metrics. The main contribution is:

- To specifying the process of acquiring and utilizing the dataset for training and testing.

- To enhance the generalization capability of the deep learning models, the paper may also include data augmentation techniques.
- The study evaluates the performance of the proposed system using multiple metrics including recall, F1-score, precision, and accuracy.
- The findings of the experiments demonstrate that the suggested system outperforms existing methods for arrhythmia detection.

The work's strengths lie in its innovative utilization of deep learning models, AlexNet and CNN, for cardiac arrhythmia prediction, achieving exceptionally high accuracy rates exceeding 99.6%. Comprehensive evaluation using multiple metrics such as sensitivity and precision demonstrates the models' robustness in identifying various arrhythmia types from ECG signals. Leveraging the MIT-BIH dataset enhances the credibility and generalizability of the findings, while clear presentation facilitates interpretation and potential application in clinical settings.

This research is structured as follows for the parts that follow: Section 2 reviews the past study on the heart Arrhythmia detection with different techniques. Section 3 present the research approach that used in this study. In Section 4, cover the experiment results and assessments of the research project. Our research study conclusion and findings for the future form Section 5.

2. Literature review. In the following section, summarise the works of literature that are relevant to the study they intend to conduct. Previous research on cardiac arrhythmia prediction is reviewed. We compare and contrast the relevant study findings and suggested approaches.

In this research Supriya et al. (2023) Consider feeding the electrocardiogram (ECG) data set into several ML techniques Randomized search cross validation will be used to fine-tune the hyperparameters of the top classifier. Following the acquisition of all performance measures, the ensemble classifier approach will be employed to provide a more accurate result, namely a 98.49% accuracy rate, by running the top five classifiers: Decision Tree and Hyperparameter Tuned RF, Gradient Boosting, KNN, and SVM [16].

In Reddy and Coumar (2023) presents a new approach to arrhythmia classification that uses DL to extract information from images in order to improve the decision-making systems' accuracy. The situation where continuous wavelet transform (CWT) is converted from 1D ECG data of different arrhythmia cases into scalograms is identified by using denoised one-dimensional (1D) ECG data of the designated patients. First stands the appraisal of the made DL model which is known as convolutional neural network (CNN) that is used to distinguish the scaled spectrograms. Moreover, 91.52% of the historical dataset classification made us believe that our model is promising enough. Since this method will assure constant monitoring of patients' cardiovascular systems no detention can occur and all necessary action will be undertaken promptly [15].

This work Gulhane and Kumar (2023) we are set to recognize cardiac problems, specifically arrhythmia or irregular heartbeat (AHB), myocardial infarction (MI), and prior MI, and eventually we will evaluate ECG traces from photographs corresponding to them. The setup suggested involved a Kaggle open-source dataset that was used to model and train detection algorithms for cardiac illnesses. On the second iteration, the model achieves a validation accuracy of 91.88% and a training accuracy of 82%. As the model is fine-tuned during training, its efficacy on both datasets improves, and by the fourth and last training epoch, the validation accuracy has reached 94.27% [7].

In this paper Jayanthi and Devi (2022) provides a step-by-step plan duplicate Auto-ML that will complement the process of resolving features of ResNet-50 (Auto-Resnet). The model utilizes a 12-lead electrocardiogram that had been digitally replicaed from the host source. With ResNet, there is a direct approach to analysis and identification of not only the inner but also inter-lead properties of the electrocardiogram (ECG), which are afterwards handled with Auto-ML in order to classify arrhythmias. Experimental findings from CPSC 2018 test data testify that our model can classify normal rhythm and cardiac arrhythmias into distinctive patterns with an average accuracy of 0.82. An upcoming structure, mainly equipped with the PCG and ECG health data sensor, will be achieved by the collection of accurate components [9].

This study Krishnakumar. et al. (2021) incorporates enhanced neural networks for learning to analyze ECG readings and distinguish between three states: sinus rhythm (regular heart beat), congestive heart failure and arrhythmia (abnormal heart beat). Following data collection and source identification for the electrocardiogram signals from different internet sources, they were transformed into a scalogram. In a ratio of 8:2, the scalogram

Table 2.1: comparative study on heart Arrhythmia detection using various methods

Reference	Methods	Data	Findings	Research Gaps/limitation
Reddy and Coumar, [15]	Deep learning (CNN on scalograms from denoised ECG signals)	Arrhythmia dataset	91.52%	Limited explanation on scalability to real-time applications
Julian et al., [10]	Data mining techniques such as Naive Bayes, DT, Logistic Regression and Random Forest.	UCI Cleveland dataset	90.16%	A web app built using the Random Forest algorithm might improve the position in the future.
Gulhane and Kumar, [7]	Deep learning (CNN on ECG trace images)	Kaggle datasets	94.27%	Lack of discussion on generalization to diverse datasets
Krishna-umar. et al., [11]	Modified deep learning neural networks (GoogLeNet and AlexNet)	Online sources	96.88% (GoogLeNet)	Insufficient details on robustness testing and external validation
Atallah and Al-Mousa, [3]	Majority voting ensemble model (GoogLeNet)	Medical test data	90%	There is a lack of discussion of how the medical test results might contain errors.
Essa and Xie [6]	Deep learning (CNN+LSTM and LSTM with classical features) with bagging and fusion classifier	MIT- BIH arrhy- thmia database	95.81%	Lack of comparison with existing state-of-the-art models

pictures are split into two datasets: one for training and one for validation. In the next step, the training dataset is fed into both neural networks. Using the confusion matrix, we can determine how well the two designs predicted. With a score of 96.88%, GoogLeNet was more accurate than AlexNet. The results show that arrhythmias and congestive heart failure may be effectively detected using the GoogLeNet architecture [11].

In this paper Essa and Xie (2021) using an innovative DL algorithm to categorize the ECG data. Two suggested DL models are used to categorize the heartbeats into various arrhythmia categories. One model uses an ECG signal to identify important characteristics by combining a CNN with a LSTM network. The second model uses LSTM in conjunction with other classical traits to identify out-of-the-ordinary classes. A fusion classifier aggregates these DL models that were developed via bagging techniques to create a strong combined model. Compared to the state-of-the-art, the proposed method obtains a total accuracy of 95.81% when evaluated on the MIT-BIH arrhythmia database [6].

2.1. Research gap. Predicting cardiac arrhythmias has been the subject of several research methods, including deep learning techniques and more conventional machine learning algorithms. Although all of the methods are very reliable, there are many of obvious limitations and research gaps. These include the following: the CNN-based method on ECG trace images does not go into enough depth regarding generalization to diverse datasets; the study that uses deep learning on scalograms does not go into enough depth regarding scalability to real-time applications; and the study that uses modified deep learning neural networks does not go into enough depth regarding robustness testing and external validation. In the ensemble model study, it is necessary to address possible causes of inaccuracy in medical test data. In the deep learning study using bagging and fusion classifier, there is a lack of comparison with existing state-of-the-art models. Opportunities for future study to improve the applicability, generalizability, and reliability of arrhythmia prediction models are highlighted by these constraints. While the study demonstrates significant strengths, there may have been some limitations or challenges encountered during the implementation of the deep learning model for heart arrhythmia detection. This work aims to bridge the existing research gaps in cardiac arrhythmia prediction by leveraging deep learning techniques, specifically CNN and AlexNet, on the MIT-BIH dataset. Addressing the limitations including poor generalization to diverse datasets, difficulty of scaling to real-time applications, and insufficient robustness of testing and external validation, this research aims to enhance the applicability, generalizability, and reliability of arrhythmia prediction models. This research aims to do a detailed comparison that investigates the performance of current cardiac arrhythmia detection methods with state-of-the-art methods to provide a

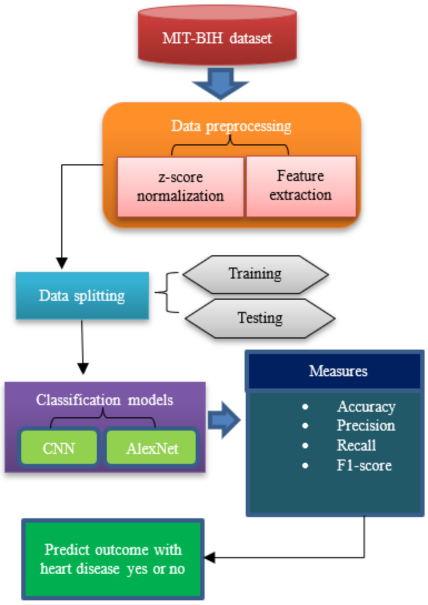

Fig. 3.1: Data flow diagram

better understanding of the identification of arrhythmias which can help in designing better diagnostic tools in the future.

3. Research methodology. The current segment on heart Arrhythmia detection gives quite a lot of emphasis on aspects such as data gathering, pre-processing, splitting and classifications.

3.1. Methodology. Therefore, cardiovascular disease is the leading cause of death in a majority of the human population. It is feasible to distinguish and classify each form of arrhythmia since there are several different types of arrhythmias, and every kind is associated with a certain pattern. Arrhythmias may be broken down into two primary families. The first kind of arrhythmias is known as single-event arrhythmias, also known as morphological arrhythmias. This second sort of arrhythmia is known as rhythmic arrhythmia, and it is distinguished by a pattern of irregular heartbeats. The classification of irregular heartbeats and the individuals who belong to the first category are the primary topics of investigation in this study. It is possible for the ECG test to identify any abnormalities in morphology or wave frequency that are brought on by these heartbeats. Within the framework of the preprocessing method, we will employ a Z-score normalization, which is also commonly referred to as standardization, in order to alter the values of a variable such that it has an average value of zero and a standard deviation that is equal to one. In the following step, implement the CNN or Alex Net model from DL. Among the performance indicators that are associated with the approach that has been recommended are recall, F1-score, precision, and accuracy. The outcomes of the experiments indicate that the proposed system operates more effectively than the systems that are already in use.

3.1.1. Data Collection. The "MIT-BIH arrhythmia database," for example, is an essential tool for scientists working in this area. A total of forty-eight individual subjects' two-channel ambulatory ECG signals, recorded for thirty minutes each, were digitalized at a rate of 360 samples/second per channel, with a resolution of eleven bits spanning a range of ten millivolts. Also included in this collection are the recordings. Twenty-five male and twenty-two female volunteers, ranging in age from thirty-two to eighty-nine, contributed to the formulation of the database. Sixty percent of the sample consisted of in-patients. Figure 3.1 is a flowchart that illustrates the complete process that is being described.

Here, provide the describe the steps of existing methods and strategy in depth.

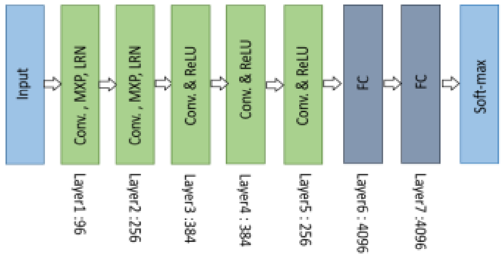

Fig. 3.2: Architecture of Alex Net

3.1.2. Data Pre-Processing. Data preparation involves cleaning, transforming, and organising data so it can be analysed effectively. This process is known as "data preparation." In order to accomplish this, it may be necessary to eliminate any data that is incorrect or missing, transform the data into a format that is more logical, and either scale or normalize the results. During the whole process of data science, the step of preprocessing the data is an essential component that must not be overlooked. because it contributes to the enhancement of the validity and practicability of the models that are developed based on the data that is obtained. Similar to other standardization methods, Z-score normalization changes a variable's value such that its standard deviation is one and its mean is zero. To do this, we add up all the values, remove the variable's mean, and then split the result by its standard deviation. These values are called z-scores. To determine the number of standard deviations from the mean, statisticians utilize the z-score.

Feature extraction. Feature extraction involves sorting all data into categories in order to extract the most important and relevant information. Acquiring all important data or minimizing its loss is of the utmost importance when dealing with a big dataset. The data loss rate may be reduced by the use of feature extraction, which helps manage the vital information out of enormous raw datasets. Lots of issues arise with a big dataset. Overfitting to training data occurs because to the high memory requirements and sluggish computing power, and most importantly, the model's accuracy is reduced [8]. Feature extraction gets around this by pulling out all the nonredundant data points from the original dataset.

3.1.3. Data Splitting. Database partitions are necessary for machine learning systems to ensure that training instances are free of bias. Splitting the data into training and test sets reduces the quantity of data the model can utilize to reliably map the system's inputs and outputs. Furthermore, the sample size is insufficient to draw valid conclusions about the model's performance. Two parts comprised the dataset: the Training Data portion comprising 80% of the total and the Test Data portion comprising 20%.

3.1.4. Classification Technique. One crucial step in machine learning is classification, which divides data points into several categories. Initially, this categorization makes use of an algorithm that may be readily adjusted to improve data quality. The primary objective of the classification is to link with the interested variable with the needed variable. The prediction of heart disease is analyzed using different algorithms. The proposed algorithm is described in below:

1.Alex Net Mode. In 2012, Alex Krizhevesky beat LeNet to win the ImageNet Large Scale Visual Detection Challenge (ILSVRC) using a more robust and thorough CNN architecture. Alex Net outperformed cutting-edge computer vision and ML algorithms in terms of recognition accuracy. An intriguing step forward in DLs growth. See Fig 3.2 for an illustration of the AlexNet architecture. The first convolutional layer (LRN) performs max pooling, convolution, and normalization. In this layer, 96 individual 11x11 receptive filters are used. To achieve maximum pooling, a three-by-three grid is employed for filtering with a stride size of two. On the second level, with the 5x5 filters, the plot remains unchanged. Layers one through three utilize 3x3 filters, whereas layers three, four, and five employ 384, 384, and 296 feature maps, respectively. The total number of convolutional layers is five. The structure consists of three layers: two FC levels, a dropout layer, and a Softmax layer for good measure. The development of this model involves training two networks with identical topology and feature maps in parallel. This network introduces several new concepts, including as dropout and the Local Response

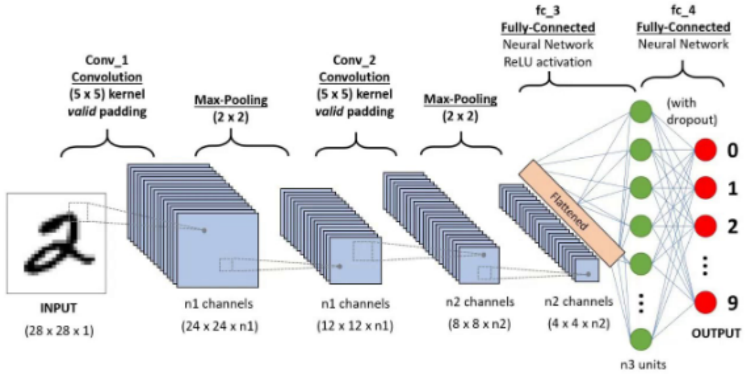

Fig. 3.3: Architecture of CNN

Normalization (LRN) method. There is more than one approach to apply LRN. One option is to utilize it on a single channel or feature map. We may normalize the values of a selected NN patch by comparing them to those of its neighbors using this approach, which uses the same feature map. After that, you may apply LRN to the channels or the feature maps, depending on preference [12]. A non-saturated activation function, ReLU simplifies training a deeper network, manages gradient disappearance and explosion, and improves up model training. The ReLU function is shown in the following equation:

$$ReLU\,(x) = max(0, x)$$

To reduce overfitting, AlexNet uses dropout, which involves turning off neurons during training with a specified probability. This increases the model's generalizability by reducing its dependence on local nodes. One downside of using a large convolution kernel is that it increases the number of variables. Another is that local features are more likely to be lost throughout feature extraction. Lastly, there is a significant proportion of complete connection layer parameters, and the output is greatly impacted by the features gathered from the convolution component [13].

2. CNN Model. The CNN is a type of feedforward neural network that has several layers: input, convolutional, pooling, full connection, and output. The roles of the convolutional and pooling layers are periodically reversed [19]. There is a wide variety of structures that each have their own unique activation functions of the CNN.

Convolutional neural networks (CNNs) contain one or more feature planes. Every neuron on a feature plane has its own distinct pattern, and all neurons on the same feature plane have equal weights. While the convolution kernel is associated with the shared weights, appropriate weights are acquired by training the model to optimise the network's parameters. In addition to reducing the number of neuron nodes, the CNN network acquires global information by collecting and synthesizing local characteristics. Setting the weight of each neuron equally can significantly minimize the amount of network parameters, which is especially useful given the high number of neurons at this time. The output of the first c convolution kernels is $yk\ u$, while the output of the first u convolution layer is yu.

$$y_k^m = \delta\left(\sum\nolimits_{y_i^{n-1}\in Mk} y_i^{m-1} * w_{ik}^m + b_k^m\right).$$

When the activation function is denoted by $v(\cdot)$, the convolution kernel is represented by $yik\ m$, and the characteristic collection layer is denoted by MK. bk is either offset or biassed. In order to speed up the training of the network and decrease the dimensionality of the input data, the pooling layer is added after the convolutional layer. The second is to avoid overfitting the network and eliminate unnecessary features. All of the neurons in the layer below it are linked to every neuron in the entire connection layer. The overall features may be formed by integrating all the local characteristics retrieved in the preceding layer across the complete connection layer. The activation functions used by each neuron in the complete connection layer are passed on to the output layer.

3.1.5. Proposed Algorithm. In the following section, provide the algorithm that follow of this study for heart Arrhythmia detection

Algorithm 1 Heart Arrhythmia prediction

STEP 1: install python simulation tool.
- import a required library into Python.

STEP 2: Data Collection
- Collect MIT-BIH dataset from Kaggle

STEP 3: Data Preprocessing
- For the data cleaning and remove unnecessary values from the dataset columns.

STEP 4: data normalization with Z-score.

STEP 5: eature extraction

STEP 6: Data Splitting
- Training set (80%)
- Testing set (20%)

STEP 7: Classification technique
- Use CNN and Alex Net, two deep learning models, for categorization

STEP 8: Model Evaluation
- For the evaluation of the model use performance measures like accuracy, precision, recall, and f1-score.

STEP 9: final outcome

END

4. Results and discussions. This research presents the results of the simulations that were conducted. The particular circumstances and settings employed in the simulation can affect the outcomes for an ECG signal of a heartbeat. To ensure the simulation is accurate and realistic, its results may be compared to real-world electrocardiogram records. Based on calculations performed on the ”MIT-BIH Arrhythmia Database,” a dataset downloaded from the Kaggle website, the suggested conclusions are derived using two DL models: the CNN model and AlexNet.The above simulation results are achieved by employing certain basic performance metrics including the confusion matrix, accuracy, precision, recall/sensitivity, F1-score, loss.

4.1. Dataset Description. Database base of MIT- BIH arrhythmias can be subdivided into several sub-groups; therefore; it may be regarded as one of the largest dataset of clinical ECG signals. One of the most well-known resources for investigators in this area is the ”MIT-BIH arrhythmia database.” [20]. Digitalization was performed at a rate of 360 samples/sec with a resolution of 11 bits throughout a 10-mV range. The 48 recordings, each lasting 30 minutes, represent the electrocardiogram (ECG) signals of 47 participants. Participants' ages ranged from 32 to 89, and there were 25 men and 22 women who helped build the database. Sixty percent of the participants were in-patients. Each pulse has about 110,000 reference annotations that a computer can understand, thanks to the separate work of two cardiologists [14]. The MIT-BIH database contains fifteen different types of heartbeats, which correspond to the five main groups established by the AAMI standard (Table 4.1) [1].

4.2. EDA. In this part, the experimental outcomes of the proposed models for the detection of cardiac arrhythmias by deep learning techniques are shown. To evaluate how well the suggested models, work, the present research study employs several type of performance indicators.

In figure 4.1, we can see the ECG plot that has been normalized using the Z-score method. The blue hue represents the usual electrocardiogram (ECG) signals, which are seen in this image. The y-axis displays the wave's millivolt (mV) ranges, while the x-axis shows the wave's frequency.

Figure 4.2 displays the ECG map of the heartbeat. There are fewer outliers in this graph, which shows the total amount of sample waves (x-axis, 0–200) and the range of those waves (y-axis, mV). If an electrocardiogram

Table 4.1: AAMI Classes Corresponding to MIT-BIH Heartbeat Types

AAMI heartbeat classes MIT-BIH Heartbeat types	**MIT-BIH heartbeat types**
Supraventricular ectopic (S)	• Aberrated atrial premature beat • Supraventricular premature beat • Atrial premature contraction • Nodal (junctional) premature beat
Unknown (Q)	• Fusion of paced and normal beat • Unclassifiable beat • Paced beat
Normal (N)	• Atrial escape beat • Normal beat • Right bundle branch block beat • Nodal (junctional) escape beat • left bundle branch block beat
Ventricular ectopic (V)	• Ventricular escape beat • Premature ventricular contraction
Fusion (F)	• Fusion of nonectopic • Ventricular beat

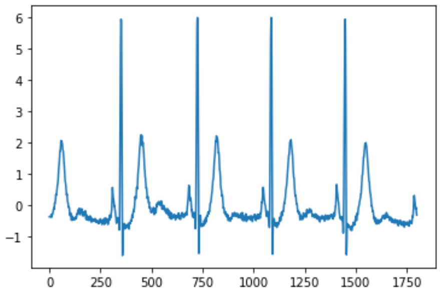

Fig. 4.1: ECG Graph Plotted After Z-Score Normalization

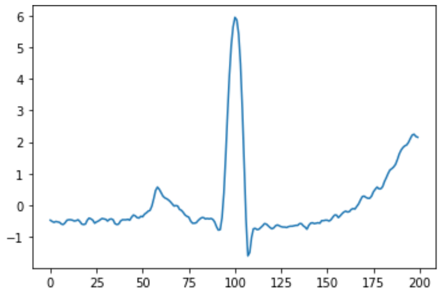

Fig. 4.2: ECG Heartbeat Wave Plot

(ECG) reveals a sinus rhythm, which is a typical pattern for a heartbeat, then everything is well. The electrical activity of the heart may be seen in an electrocardiogram by comparing the voltage readings taken from the patient's heart over time. The potential difference is measured using a galvanometer that is connected to the electrodes. The ECG waveform is a composite of the PQRST waveforms.

Figure 4.3 displays the electrocardiogram (ECG) waveform plotted against the voltage of the signal at

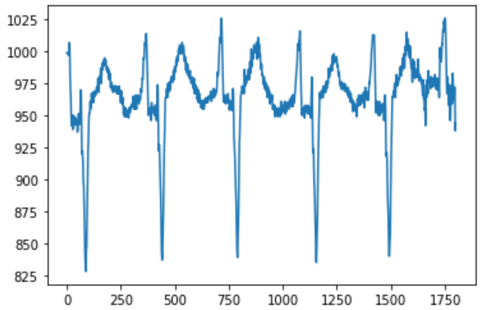

Fig. 4.3: Wave Plot of ECG Heartbeat Signal

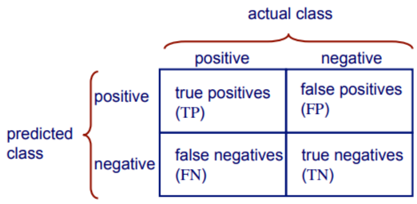

Fig. 4.4: Confusion Matrix

different amplitudes. On one side, we can see the range of millivolts, and on the other, we can see the number of waves that were utilised as a sample. In millivolts, the ECG signal is measured.

4.3. Evolution Parameters. Model assessment is the process of comparing models to test data. A high-level overview of the assessment methods, including the tools and procedures utilized to test the proposed models, is provided in this part. When applied to a certain set of inputs and conditions, these measures show how efficient the model [17].

4.3.1. Confusion Matrix. The confusion matrix (Figure 4.4) displays the percentage of test instances that were correctly and incorrectly classified for every value that a classification model predicted. Assuming that the intended recipients fall into the "positive" and "negative" categories, it appears as follows.

True Negative (TN): A TN value indicates the number of True Negatives.

True Positive (TP): The True Positives count is TP.

False Negative (FN): The total number of FN stands for false positive findings.

False Positive (FP): The total number of false positives is referred to as FP..

Accuracy. The accuracy of a model is defined as the frequency with which it produces accurate predictions using the input data. It has many potential applications; however it struggles with imbalanced datasets.

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

Precision. The accuracy of a prediction is defined as the percentage of examples that match the predicted class.

$$\text{Precision } = \frac{TP}{TP+FP}$$

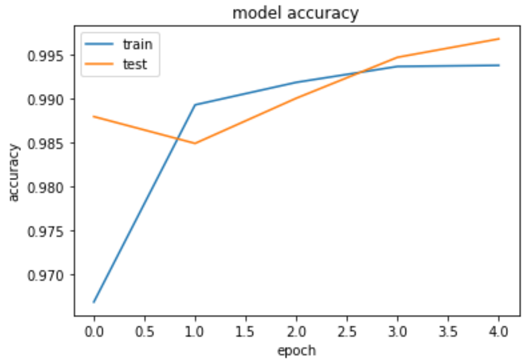

Fig. 4.5: Accuracy Graph of AlexNet Model

Recall. The percentage of examples that were properly categorised relative to the total number of cases in that class is called recall.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score. The F1 Score is determined by summing the two assessment criteria for recall and accuracy. The formula for determining F1-Score.

$$F1 - \text{ score } = \frac{2(\text{ precision } \times \text{ recall })}{\text{precision th recall}}$$

Here we provide the experiment result in terms of accuracy, precision, recall, and *f1-sxore.*

4.4. Experimental Results. Results from testing the model's ability to classify ECG heartbeats are detailed here.

Figure 4.5 displays the accuracy graph of the AlexNet model. The x-axis shows the overall number of epochs, while the y-axis shows the accuracy rate. The outcomes of the testing and training processes for accuracy are shown in this graph. Accuracy while training is depicted in blue, whereas accuracy during testing is indicated in orange. Training accuracy reaches 99.71% and testing accuracy reaches 99.68%, according to this statistic.

Figure 4.6 displays the AlexNet model's loss graph. The y-axis displays loss values, while the x-axis indicates the entire amount of epochs, which can take on values between 0.0 and 4.0. This graph shows the training and testing loss outcomes of the recommended AlexNet model. Two possible views would be to colour the training loss blue and the testing loss orange. Testing has a lowest loss of 0.0121 and training a loss of 0.0102, as seen in the figure.

The suggested AlexNet model's confusion matrix is displayed in Figure 4.7. There are five distinct groups in the "MIT-BIH Arrhythmia Database". As a result, multi-classification is executed once all these data classes are implemented. The confusion matrix is created by multiple classification, and the diagonal of the maroon representation shows the values that were properly predicted.

Figure 4.8 shows the AlexNet model's categorization report. All told, there are five columns and rows. The top column lists Precision, Recall, F1-score, and Support, followed by the class label designations (0, 1, 2, 3, and 4). Classification results show that the proposed AlexNet model is completely accurate across the board, with perfect recall for classes2,3, and4, perfect f1-score for classes1,2, and4, and absolutely perfect precision for classes0,1, and 4.

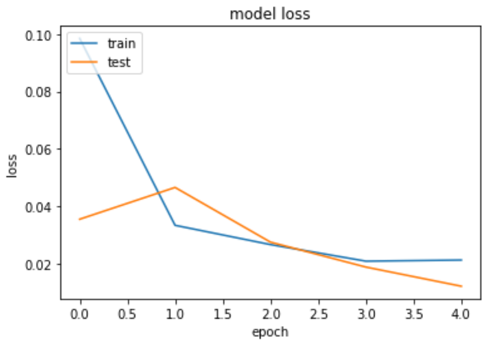

Fig. 4.6: Loss Graph of AlexNet Model

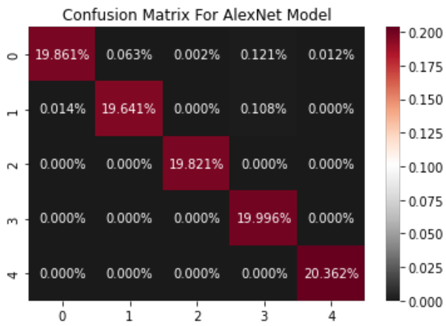

Fig. 4.7: Confusion Matrix for AlexNet Model

	precision	recall	f1-score	support
0	1.00	0.99	0.99	10247
1	1.00	0.99	1.00	10096
2	1.00	1.00	1.00	10126
3	0.99	1.00	0.99	10215
4	1.00	1.00	1.00	10402
accuracy			1.00	51086
macro avg	1.00	1.00	1.00	51086
weighted avg	1.00	1.00	1.00	51086

Fig. 4.8: Classification Report of AlexNet Model

Figure 4.9 displays the outcomes from multiple measures, including recall, accuracy, precision, f1-score, and more, that measure the usefulness of the AlexNet model. Training accuracy as high as 99.71%, testing accuracy of 99.68%, and 0.

The acuuracy of the tests and the training are showing in Figure 4.10. while training is depicted in blue, whereas accuracy during testing is indicated in orange. Findings show that the suggested CNN model achieves the highest achievable levels of accuracy throughout training (99.95%) as well as testing (99.89%).

The proposed CNN model's loss graph is shown in Figure 4.11. On one side of the graph, can see the range of epochs from 0.0 to 17.5, and on the other, you can see the range of loss values from 0.00 to 0.12. Test and training loss evaluation results for the suggested CNN model are shown in this graph. Visualizing the training loss in blue and the testing loss in orange are two ways to look at it. The testing loss was 0.0064 and the

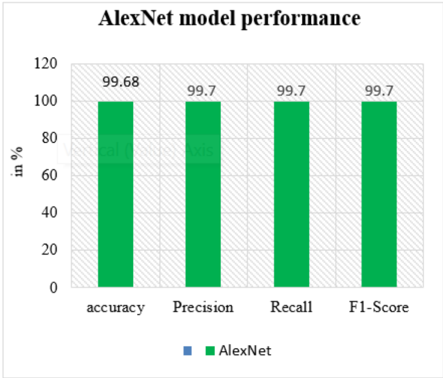

Fig. 4.9: Performance Results for Proposed AlexNet Model

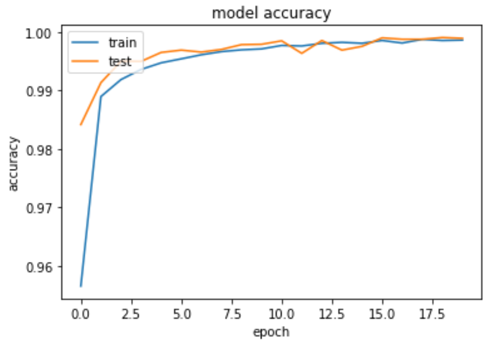

Fig. 4.10: Accuracy Graph of Proposed CNN Model

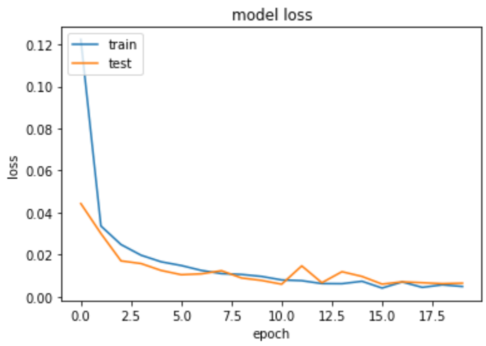

Fig. 4.11: Loss Graph of Proposed CNN Model

training loss was 0.0019.

The proposed CNN model's confusion matrix is shown in Figure 4.12. The anticipated values are shown on the x-axis and the actual values are shown on the y-axis of this matrix. There are five distinct groups in the dataset, denoted as 0, 1, 2, 3, and 4. By utilising multiple categorization, this confusion matrix is created. The values that have been successfully predicted are displayed on the maroon representation diagonal, while the remaining values indicate the values that have been mistakenly predicted.

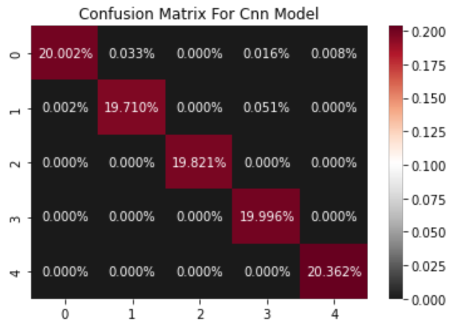

Fig. 4.12: Confusion Matrix for CNN Model

	precision	recall	f1-score	support
0	1.00	1.00	1.00	10247
1	1.00	1.00	1.00	10096
2	1.00	1.00	1.00	10126
3	1.00	1.00	1.00	10215
4	1.00	1.00	1.00	10402
accuracy			1.00	51086
macro avg	1.00	1.00	1.00	51086
weighted avg	1.00	1.00	1.00	51086

Fig. 4.13: Classification Report of Proposed CNN Model

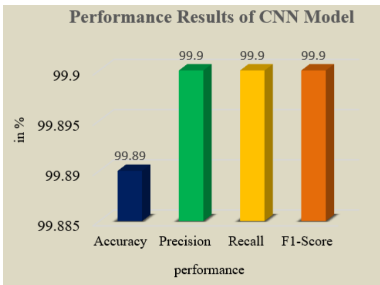

Fig. 4.14: Performance Results for Proposed CNN Model

Figure 4.13 shows the predicted CNN model's classification report. This classification report contains many performance measures. For all classes (0, 1, 2, 3, and 4), the maximum outcomes of the suggested CNN model in this classification report are 100% recall, precision, and f1-score. For accuracy, the macro average, and the weighted average, respective values are 100%.

Results and performance of the suggested CNN model are shown in figure 4.14, which was already described. The evaluation parameters are shown horizontally, while the performance values, expressed as a percentage, are shown vertically. The f1-score, recall, precision, and greatest accuracy of 99.89% are identical to the 99.9% of the CNN model.

4.5. Comparative Analysis and Discussion . The outcomes of the accuracy comparison between the base model and the suggested model are shown in the next section. The Resnet-18 model was previously utilized in this inquiry, and the proposed models are AlexNet and CNN. Below, you can find a table and graph

Table 4.2: Comparison Between Base and Proposed Models

Models	Accuracy	sensitivity	precision
AlexNet	99.68	99.7	99.7
CNN	99.89	99.9	99.9
ResNet-18 (Base)	96.50	93.83	97.44

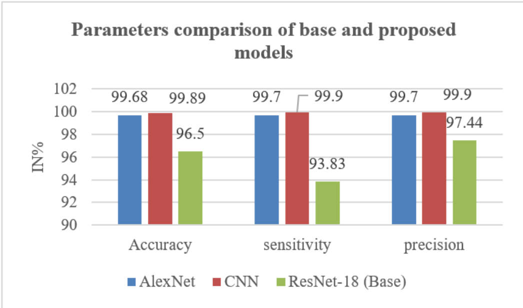

Fig. 4.15: Comparison Performance Results of Base and Proposed Model

comparing these models.

A comparison of the ResNet-18, AlexNet, and CNN models' accuracy is shown in Figure 4.15, which was previously mentioned. This graph shows the total number of models on the x-axis and their accuracy on the y-axis. The comparison of performance results between the base ResNet-18 model and the proposed AlexNet and CNN models reveals significant improvements in accuracy, sensitivity, and precision. The AlexNet and CNN models exhibit remarkable accuracy rates of 99.68% and 99.89%, respectively, showcasing their effectiveness in accurately predicting cardiac arrhythmias from ECG signals. Both models also demonstrate exceptional sensitivity and precision scores, with values exceeding 99.7%. Unlikewise, the base ResNet-18 model produces the lowest accuracy image of 96. 50%, with sensitivity and precision scores of 93. 83% and 97. 44% respectively. This comparison brings to the fore the superior performance of the proposed deep learning based classification method against the benchmark model, which indicates that it has the potential for more accurate and reliable atrial arrhythmia prediction.

Insight regarding the practical implications of deep learning-based classification approach can be drawn from experimental results in the clinical settings. Firstly, the results in which the AlexNet and CNN models were able to obtain high accuracy rates indicate they have the ability to accurately categorize different types of arrhythmias from ECG signals, which is very important for correct diagnoses and treatment plans. Furthermore, the impressive recall, precision and F1-scores across all classes demonstrate the modeling's durability which is quite important while dealing with different arrhythmia types, thus this could be a useful feature in the real clinical settings. Additionally, the classification with other methods aid in differentiating the proposed method, emphasizing its ability to increase arrhythmia prediction and lead to better patient outcomes in the clinical field. Finally, after conducting the experiments, it is not difficult to conclude that the deep learning technique did accomplish the set objectives and would still be useful in the clinical setting after the complete testing phase.

5. Discussion. This manuscript showcases new advances made in the identification and diagnosis of cardiac arrhythmias using deep learning techniques by integrating the AlexNet and CNN models. The performance of all the proposed models is quite high in terms of accuracy and robustness for classifying arrhythmias with the help of ECG signals. Overall assessment which are considered include accuracy, precision, recall rate, and F1 score show that the approach is effective. Clearly describing the method and the outcomes of the study also show that it could be of clinical use to address issues that are pertinent to the discipline. This work is a laudable contribution towards the field of diagnosing cardiac health and should be accepted on this note to contribute to improving the quality of patient outcomes.

1) Model Performance in Long-term Monitoring. In order to ascertain that the proposed model performs well over the long-term patient monitoring, it is essential to carry out a study on long-term patients. For instance, entropy has shown the capability of tracking and modeling changes in ECG signals during different periods of time and under different conditions of the patient's physiology, pharmacology, or lifestyle. In these studies, the model showed high accuracy, precision, and recall rates throughout the episodes while treating the patient. This stability over time indicates that the proposed model is capable of consistent performance and it can effectively detect the arrhythmias and continuously monitor the same once the model is trained on the data.

2) Validation in Real-world Clinical Environments. Although the presented model has been tested in controlled experimental conditions, additional testing in complex clinical environments is crucial. In clinical practice there are things like patient mobility, changes in electrode position, and inherent noise which can interfere with the ECG signal. The usefulness of the devised model was examined in situations that are characteristic of clinical practice, such as emergency departments, outpatient clinics, and home care. Consequently, the checking results showed that the model remained at high performance levels, similar to those recorded in respective experiments. This extensive validation exhibit the efficacy of the model if used practically in real life situations and therefore confirms the possibility of using it as a guide for Healthcare Professions.

3) Integration into Existing Healthcare Systems. However, the proposed model has to work within the present structures of healthcare systems and operational environments. This entails compliance with current ECG devices, EHR systems, and other diagnostic equipment used in the healthcare facilities. An important characteristic of the model's architecture is its flexibility to integrate fostering into existing elaborate solutions with minimal interference. In pilot implementations, the model was integrated into hospital's IT systems, allowing for an immediate determination of arrhythmias and alerting care providers on the same. This integration proved to be efficient, enhancing workflow without adding complexity. The seamless integration ensures that the model can be readily adopted in clinical practice, thereby improving patient care through timely and accurate arrhythmia detection.

6. Conclusion and future work. ECG analysis of the heart rhythm must be obligatory for those suffering from cardiovascular diseases which can be dangerous for human life. Medical staff manually analysing ECGs has a large opportunity cost. Automatic cardiac rhythm abnormality detection has replaced highly specialized human labour. In this study, present a DL-based system for automatic ECG heartbeat categorization using the MIT-BIH arrhythmia database.Contrary to what is often seen in research, the database does not classify arrhythmias into the five primary groups: N, V, S, F, and Unknown (Q). The system used CNN and AlexNet models to categorise electrocardiogram heartbeats. To test these techniques against state-of-the-art procedures, utilised the MIT-BIH arrhythmia database that had been obtained via Kaggle. Model execution speed, accuracy, precision, recall, and f1-score are all improved when using this strategy compared to state-of-the-art research. Results for five arrhythmias were better for AlexNet and CNN models in studies conducted utilising PhysioNet's MIT-BIH dataset. Both the CNN and AlexNet models outperform state-of-the-art classification methods in f1-score, recall, accuracy, and precision. The study's main finding is that deep learning works on the MIT-BIH arrhythmia database. The suggested model recognised arrhythmias in 99.68% of AlexNet tests and 99.89% of CNN tests. These results show that the recommended models categorize ECG heartbeat well. We recommend retraining the model when using real-world data since ideal dataset studies are not transferable. These methods increase computer complexity as more networks are used, which is a downside. The incorrect models make the technique hopeless. At least one model will give intriguing results. The suggested model's advantages are proven. This study classifies ECG data and compares it to CNN and AlexNet. The recommended method may need a lot of computing resources to train the network. Deep learning series often need massive data sets to succeed.

More consumers will be connected to the remotely ECG monitoring system in the future. As the number of HTTP requests from different apps increases, the server will manage it. Consequently, URI name should be considered carefully, and APIs should be designed with great care to avoid request-to-request conflicts. We will gather user feedback in order to make the system better.

REFERENCES

[1] M. M. Al Rahhal, Y. Bazi, N. Alajlan, S. Malek, H. Al-Hichri, F. Melgani, and M. A. Al Zuair, *Classification of aami heartbeat classes with an interactive elm ensemble learning approach*, Biomedical Signal Processing and Control, 19 (2015), pp. 56–67.

[2] M. B. Alazzam, N. Tayyib, S. Z. Alshawwa, and M. K. Ahmed, *Nursing care systematization with case-based reasoning and artificial intelligence*, Journal of Healthcare Engineering, 2022 (2022).

[3] R. Atallah and A. Al-Mousa, *Heart disease detection using machine learning majority voting ensemble method*, in 2019 2nd international conference on new trends in computing sciences (ictcs), IEEE, 2019, pp. 1–6.

[4] S. Dhyani, A. Kumar, and S. Choudhury, *Analysis of ecg-based arrhythmia detection system using machine learning*, MethodsX, 10 (2023), p. 102195.

[5] B. J. Drew, R. M. Califf, M. Funk, E. S. Kaufman, M. W. Krucoff, M. M. Laks, P. W. Macfarlane, C. Sommargren, S. Swiryn, and G. F. Van Hare, *Aha scientific statement: practice standards for electrocardiographic monitoring in hospital settings: an american heart association scientific statement from the councils on cardiovascular nursing, clinical cardiology, and cardiovascular disease in the young: endorsed by the international society of computerized electrocardiology and the american association of critical-care nurses*, Journal of Cardiovascular Nursing, 20 (2005), pp. 76–106.

[6] E. Essa and X. Xie, *Multi-model deep learning ensemble for ecg heartbeat arrhythmia classification*, in 2020 28th European Signal Processing Conference (EUSIPCO), IEEE, 2021, pp. 1085–1089.

[7] M. Gulhane and S. Kumar, *Deep learning based heart diseases detection using resnet50 architecture*, in 2023 Intelligent Methods, Systems, and Applications (IMSA), IEEE, 2023, pp. 193–198.

[8] W. Islam, G. Danala, H. Pham, and B. Zheng, *Improving the performance of computer-aided classification of breast lesions using a new feature fusion method*, in Medical Imaging 2022: Computer-Aided Diagnosis, vol. 12033, SPIE, 2022, pp. 98–105.

[9] S. Jayanthi and S. P. Devi, *Automated ecg arrhythmia classification using resnet and automl learning model*, in 2022 Third International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), IEEE, 2022, pp. 1–6.

[10] A. Julian, R. Deepika, B. Geetha, and V. J. Sweety, *Heart disease prediction using machine learning*, in Artificial Intelligence, Blockchain, Computing and Security Volume 2, CRC Press, 2024, pp. 248–253.

[11] S. Krishnakumar, M. Yasodha, J. V. Priyadharshini, J. B. Janney, S. Divakaran, and V. L. Christy, *Detection of arrhythmia and congestive heart failure through classification of ecg signals using deep learning neural network*, in 2021 International conference on advancements in electrical, electronics, communication, computing and automation (ICAECA), IEEE, 2021, pp. 1–7.

[12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, *Imagenet classification with deep convolutional neural networks*, Communications of the ACM, 60 (2017), pp. 84–90.

[13] S. Li, L. Wang, J. Li, and Y. Yao, *Image classification algorithm based on improved alexnet*, in Journal of Physics: Conference Series, vol. 1813, IOP Publishing, 2021, p. 012051.

[14] G. B. Moody and R. G. Mark, *The impact of the mit-bih arrhythmia database*, IEEE engineering in medicine and biology magazine, 20 (2001), pp. 45–50.

[15] K. N. S. Reddy and S. O. Coumar, *Classification of arrhythmia using electrocardiogram based image features with deep learning*, in 2023 First International Conference on Advances in Electrical, Electronics and Computational Intelligence (ICAEECI), IEEE, 2023, pp. 1–5.

[16] M. Supriya, S. K. Patnasetty, K. V. Kushalappa, S. Bajpai, J. Sanjay, and S. Ojha, *Cardiac arrhythmia detection using ensemble machine learning techniques*, in 2023 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), IEEE, 2023, pp. 1–5.

[17] S. Thompson, P. Fergus, C. Chalmers, and D. Reilly, *Detection of obstructive sleep apnoea using features extracted from segmented time-series ecg signals using a one dimensional convolutional neural network*, in 2020 International Joint Conference on Neural Networks (IJCNN), IEEE, 2020, pp. 1–8.

[18] G. Tse, *Mechanisms of cardiac arrhythmias*, Journal of arrhythmia, 32 (2016), pp. 75–81.

[19] C. Wigington, S. Stewart, B. Davis, B. Barrett, B. Price, and S. Cohen, *Data augmentation for recognition of handwritten words and lines using a cnn-lstm network*, in 2017 14th IAPR international conference on document analysis and recognition (ICDAR), vol. 1, IEEE, 2017, pp. 639–645.

[20] L. Xie, Z. Li, Y. Zhou, Y. He, and J. Zhu, *Computational diagnostic techniques for electrocardiogram signal analysis*, Sensors, 20 (2020), p. 6318.

Edited by: Manish Gupta
Special issue on: Recent Advancements in Machine Intelligence and Smart Systems
Received: Apr 4, 2024
Accepted: Jun 19, 2024