Arrhythmia Classification for Non-Experts Using the IIR Filter in Machine Learning and Deep Learning Models from Electrocardiograms

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ABSTRACT

Arrhythmias are the leading cause of cardiovascular morbidity and death. For decades, portable electrocardiogram (ECG) monitors have assisted people suffering from periodic cardiac arrhythmias. These monitors give real-time data on cardiac activity to identify irregular heartbeats. ECG analysis is challenging even for experienced practitioners, and "rhythm observation and detection of waves, particularly abnormalities in the 12-lead ECG, are difficult to correlate with the patient's condition and make a correct diagnosis." All of this is due to noise in the ECG readings. It is simpler to examine noise when the frequencies at which it occurs are removed or reduced. The primary purpose of this research is to eliminate interference from power line noise by using a low-order infinite impulse response (IIR) filter to resolve baseline uncertainty and enhance the quality of the ECG signal. This allows the acquired data to be easily evaluated and classified as rhythms. In this work, ECG signal data from the The Massachusetts Institute of Technology-Beth Israel Hospital(MIT-BIH) Database is utilised to demonstrate a novel method of classifying cardiac arrhythmias based on IIR filter design. We used several machine learning (ML) and deep learning (DL) approaches to examine the filtered data for this. This research also looked at the categorization of arrhythmias using different filters as well as the changes in accuracy. As a consequence, when all models were evaluated, DenseNet seemed to get higher outcomes at 99%.

INTRODUCTION

Hearts are vital organs. Blood flow controls organ function (5). The majority of people worldwide are killed by HD. The AHA says American Indians have the highest rate of heart disease. Heart disease is more common in women over 65 (41). HD is a group of heart and blood vessel diseases (30). Heart arrhythmia are a common cardiac illness . Arrhythmia affects the heartbeat. It indicates a fast, slow, or irregular heartbeat. Tachycardia is a rapid heartbeat. Atrial fibrillation is the most common arrhythmia (29). ECGs are one of the easiest ways to check heart rhythm. Portable Holter monitors record electrocardiograms. It can record 24-hour ECG signals (14). ECG signals can easily detect arrhythmia. Millions of people have irregular heartbeats, which can be dangerous. Thus, accurate, low-cost arrhythmic heartbeat diagnosis is desirable. ECG signals, which show heart electrical activity in P, QRS, and T waveforms, have been used to classify arrhythmia by many researchers. Time, size, and distance between waves and peaks determine heart arrhythmia. Feature extraction and beat classification help diagnose arrhythmia.

In recent years, a variety of approaches have been developed for categorising ECG data. Classification accuracy for electrocardiograms (ECGs) depends on classifier capability and ECG feature identification abilities(3). Device power interference is another potential source of noise in electrocardiogram recordings , baseline drift (low-frequency signal variation), skin-electrode contact noise, and motion artefacts (a patient issue that occurs when the patient moves on purpose or by accident while the ECG is being taken). Motion artefacts from patient muscle movement, even safe movement, can be misinterpreted as arrhythmia. ECG signals change frequency over time. Thus, nonlinear noise and artefacts affect ECG signals (21). Ambulatory electrocardiograms (AECG) have grown significantly compared to 24- to 48-hour Holter monitoring systems. AECGS can last from 30 seconds to 30 days. AECGs range from full-scale 12-lead electrocardiograms (ECGs) to small patches with narrow vectors. Beyond arrhythmia analysis, AECGs are used clinically. They are now used to classify and predict risk and study ST level and QT interval shape (44).

Most ways to classify arrhythmia use ECG patterns, either in the domains of time and frequency. Several details from this ECG picture are used to figure out the type of beat (37). In short, here are some of the biggest problems with classifying ECG arrhythmia:

- It is important to have a reliable way to mark heartbeats and measure features. Most likely, the signs of arrhythmia won't be seen when the ECG signal is being taken (39).
- People's ECG signals are different because their intrabeat and interbeat time amplitudes are different and way of life. It is hard to find a general framework for classifying heartbeats that can be used with a larger population (40).
- In the temporal-frequency domain, the way arrhythmia shows itself is random. So, the ECG signal study might have to be done for a longer time, which would give more information. Because of this, tachycardia is more likely to be wrongly diagnosed (18).
- Noise and other unwanted parts can mix and cover morphological patterns, making it harder to tell what kind of heartbeat it is (45).

We work based on computer-aided diagnosis system. that helps cardiologists diagnose arrhythmia in a smart, efficient, and cost-effective way using ECG. To reach this goal, the patterns of ECG are characterised using the most up-to-date machine learning and deep learning methods. The suggested method can clearly define and identify four29 types of heartbeats that are grouped into 28 different cardiovascular arrhythmia. The rest of the heartbeats are normal. So far as we can tell, our method is the first one that can classify such a huge number of heartbeats, especially cardiac arrhythmia.This study shows a new way to classify arrhythmia from ECG by relying on different ML and DL methods, and it is based on the idea of a hybrid classification scheme. First, we filter the data by preprocessing, thereby making the classification of the signals easier. In this way, we will classify the ECG signals into ML and DL models.

This paper is organised as follows: The first section goes over the introduction in detail. The relevant research findings are summarised in Section 2, where they are used to forecast the severity with which arrhythmia would occur. The basics of machine learning and deep learning are broken down and addressed in Section 3, which is titled "materials and methods." In addition, information regarding the model results is found in Section 4. In Section 5, the performance discussion of the IIR filter in comparison to filters of other types are presented. Section 6 contains an explanation of the conclusions as well as any new features.

RELATED WORK

The most common type of heart disease is an arrhythmia, which means that the heart beats in a way that isn't normal. Electrocardiogram (ECG) signals are used to find out what's wrong with the heart when arrhythmia is present. But there are other problems besides the fact that the ECG signals don't stay in the same pattern. It is hard to get a good signal from an electrocardiogram (ECG) because of things like interference from power lines, baseline drifting, motion artefacts, and electromyogram noise. Since the ECG signal is not stable, the only way to get rid of these noises from the ECG signal is to get rid of them. After the ECG signals have been cleaned up in this way, it is easy to put them into different groups (20). Many traditional classification models are being used to handle this issue. Random Forest and Support Vector Machine (RF and SVM) (6), k-nearest neighbours (KNN) (36), and Artificial Neural Networks with Logistic Regression are the most common methods (ANN with LR) (34). Different methods, like decision trees (22), hidden Markov models (33), and hyperbox classifiers (15), are also used to classify arrhythmia. In the past few years, researchers have been using deep learning more and more to pull out features. Researchers have used DL models of CNN (2), CNN-LSTM (12), LSTM-AE (16), and BiLSTM (23) models of neural network convolution to classify irregular heartbeats. In reality, researchers have to do a lot of work to get features, and sometimes the features they make by hand can't accurately describe an electrocardiogram. Deep learning is much better than machine learning at recognising objects, analysing time series data, classifying images, etc. Deep learning has made a lot of progress recently that has helped make health care better. Deep learning does a great job with a lot of data, as has been shown. Deep learning can save time when it comes to extracting features and doesn't require a lot of related knowledge, which makes it very efficient. Researchers classify ECG data and find out how well it can be transferred by looking at Alex Net, VGG-16, ResNet-50, and the Inception CNN network topologies . In most cases , CNN's network topologies work better than those of other networks, but it takes other networks longer to process the same data, which is not practical. Aside from that, though, the ECG data is not well balanced because there aren't many negative samples. So, data that isn't balanced could change the final classification (4).These things are included in the table 1 below.

Table 1. The study that is related to the classification of ECG signals.

Ref	Researcher/ year	Data$_s$*ources*	Method	Extracted features	Approaches to Classification	Accuracy / F1 Score
[14]	Nesrine 2022	PhysioNet CinC 2011	Multi-objective optimization (MOO) method	Statistical Frequency domain and Time domain features	KMeansSMOTE and SMOTETomek	KMeansSMOTE : 0.918 SMOTETomek : 0.8936
[15]	Shreya 2021	MIT-BIH arrhythmia dataset	Ensemble of RF and SVM	Spectral Features , Statistical Features and Temporal Features	Random Forest (RF) SVM Ensemble RF + SVM	98.21
[16]	Sinha 2022	MIT-BIH arrhythmia dataset	Empirical Mode Decomposition	Multilayer Similarity Coefficients, Time Frequency Variation and Phase Synchrony Features	DNN :Deep Neural Network LS-SVM :Linear Square SVM	DNN :99.05 LS-SVM :98.82
[17]	Sanjay 2020	MIT-BIH arrhythmia dataset	General sparsed neural network (GSNN)	Time Domain Features Frequency Domain Features High Level Features	General sparsed neural network (GSNN)	0.98
[18]	Rajani 2022	MIT-BIH arrhythmia database	Adaptive boosted optimized DT classifier	Temporal Features Morphological Features	Optimized DTAdaptive boosted optimized DT	Optimized DT :97.30 Adaptive boosted optimized DT :98.77
[19]	Sadoughi 2022	MIT-BIH arrhythmia database	The Hidden Markov Model (HMM)	Time Series Featutres	Layered Hidden Markov Model (LHMM)	97.10
[20]	Hosseinzadeh 2021	MIT-BIH, EDB, AHA, CU, NSD, University of Toronto Dataset (UofTDB)	Multi Class SVM	Time Domain Features , Frequency Domain Features Authentication Features,	SVM + ANN	95
[21]	ZEESHAN 2021	MIT-BIH Arrhythmia database PTB Diabostic ECdataset	Multimodal Feature Fusion (MFF)	Frequency Domain Features	Multimodal Image (MIF) and Feature Fusion (MFF).	MIF : 98.4 MFF ; 99.2
[22]	EHAB ESSA 2021	MIT-BIH arrhythmia database	An Ensemble of DL-Based Model	RR frequencies, higher-order statistics (HOS)	CNN-LSTM and RRHOS-LSTM networks	CNN RRHOS:99.25 LSTM :95.81
[23]	Borui 2020	MIT-BIH Arrhythmia Database	LSTM-Based Auto-Encoder	Beats-based Features Record based Features	SVM	99.45
[24]	Hongqiang 2022	MIT-BIH arrhythmia database	Bidirectional LSTM (BiLSTM) network	End to end	bidirectional LSTM (BiLSTM)optimized Bayesian	99.00%
[25]	Amin Ali 2022	MIT-BIH and PTB Diagnostic db	1D and 2D CNN model	Greatest Features	LSTM	99.21

In the investigation, we developed a new design with a cost-sensitive loss function and built the dense net model, which is a type of convolutional neural network with dense links between layers. This is done with dense blocks, where all layers with the same size feature maps are connected directly to each other. The final result shows that the new method can improve accuracy without any extra work from humans and save a lot of time compared to methods that are already in use.

MATERIALS AND METHODS

This part talks about the database that was used, the preprocessing step, how the heat beats were found, how the classes were matched and given names, and how the classes were put together.

0.1 Arrhythmia Database

The MIT-BIH arrhythmia database was used for this study; it is a public standard dataset. And it contains 48 separate 24-hour, two-channel ECG recordings, each lasting 30 minutes. Annotation of each file Heartbeat types are catalogued in the ATR file. According to ANSI/AAMI EC57:1998/(R) 2008, there are 18 different original beat types in the MIT-BIH arrhythmia data, including normal (N), supraventricular ectopic (S), and ventricular ectopic (V). Q, F, and M. (V) beat the clock. Table 2 displays the sample sizes used in this analysis (Rexy et al.).

Categories of ECG signals

The Association for the Advancement of Medical Instrumentation (AAMI) categorises heartbeats as normal (N), supraventricular ectopic beat (SVEB), ventricular ectopic beat (VEB), fusion beat (FB), and unknown beat. Normal heartbeats are denoted with the letter "N," while abnormal heartbeats are denoted with the letters "S" "V" ,"F" and "Q". The range of 60–100 beats per minute is considered normal(38). Figure 1 shows examples of these five ECG signal categories.

Table 2. Beats and Classes of the Heart's Rate (Rexy et al.)

AAMI Heartbeat Classes	MIT-BIH Heartbeat Classes	No of Beats Available
Non-ectop Beats(N)	N,L,R,j,e	74776,8052,7239,229,16
Supraventricular ectopic Beats (S)	A,a,S,J	2528,149,2,83
Ventricular ectopic Beats (V)	!,V,E,[,]	472,7115,106 ,6,149
Fusion Beats(F)	F	106
Unknown beats (Q)	f,/,Q	979,7001,33

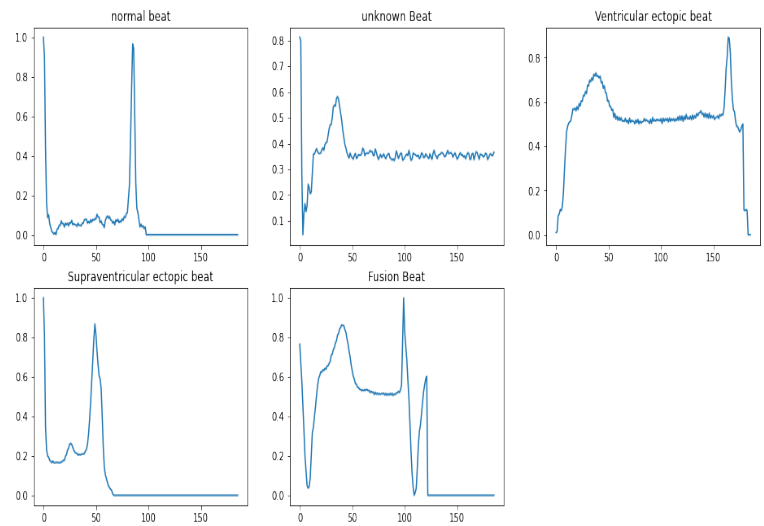

Figure 1. ECG signal samples of five classes (38).

ECG Data Pre-Processing

All ECG signals must be preprocessed to remove artefacts such as baseline drift, motion artefacts, muscle noise, and power line interfaces. During data preparation, unstructured data is transformed into a more manageable format. This is also a crucial data mining step, as we cannot do anything useful with the raw data. Before using machine learning or data mining methods, it is important to verify the integrity of the data. For this, we used an IIR filter to remove noise from raw ECg signals (8).

Algorithm for IIR Filter Design

The steps of the IIRFILTER algorithm are detailed below.

- Arrhythmia-related ECG data consists of 48 channels;
- Define ECG features;
- The QRS (t) interval is standardised at 0.098 seconds, and the sampling frequency Fs is set at 500 hertz.
- Baseline wondering employs a high-order IIR filter of 60th order; We designed the optimal IIR low-pass filter with a frequency cutoff of 150 Hz. For a passband Butterworth filter, a high- and low-cutoff frequency, FL and FH, respectively, are developed.
- Power line interference may be prevented using an IIR stop band filter with a coefficient of 100;
- The average heart rate is calculated by adding regular and irregular heart rates together.

The ECG results after using the IIR filter are shown in the figure 2 below

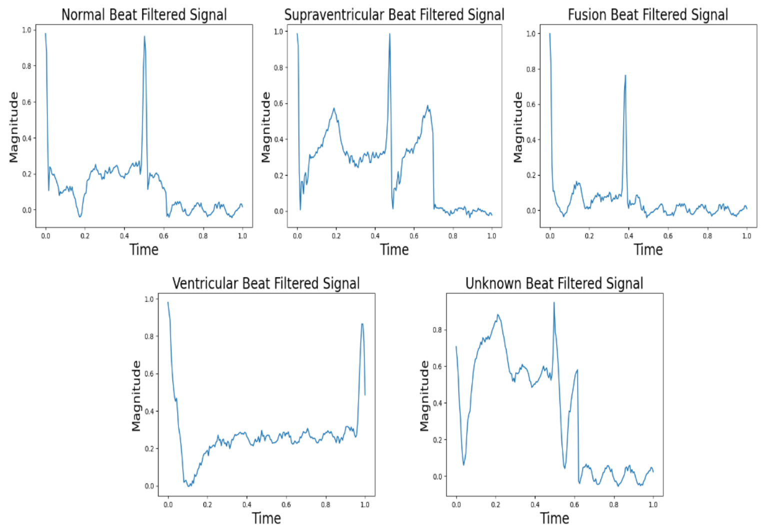

Figure 2. Filtered ECG Signals .

Balance of Database with SMOTE

Inconsistencies in the MIT-BIH arrhythmia database are common, with more ”normal” cases than ”interesting” or ”abnormal” cases. Classification algorithms may prefer the majority class (more observations) than the minority class (less observations) when making predictions. The majority has many observations, so the truth is hidden. Misclassifying ”abnormal” cases as ”normal” in medical applications can be fatal. Classifiers must strike a balance to learn their jobs. Before balancing the arrhythmia database, MIT-BIH has the following observations (13). This is shown in the figure 3 below.

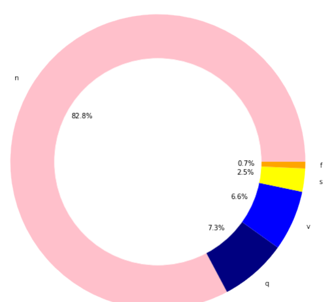

Figure 3. Architecture of the imbalance database (13).

SMOTE

The approach for balancing datasets oversamples the minority classes (SVEB (S), VEB (V), F, and Q) in order to match the sample size of the sample from the majority class (N). The proposed method assumes SMOTE oversampling. SMOTE creates synthetic feature space examples to oversample minority classes, unlike replacement methods. Operations that are particular to the feature space reduce oversampling dependence. Synthetic examples are created for each minority class sample (k = 5). First, calculate the difference between the sample's nearest neighbour (xzi) and itself (xi) (35). Multiply the difference by a random number 0 to 1. The SMOTE-resampled database results are as follows:

The MIT-BIH database presents the five AAMI-recommended arrhythmia categories (N, V, S, F, and Q) in a specific and common manner. The database contains training and testing samples. We use some of these two samples as training data and perform SMOTE data preprocessing on the rest. The SMOTE results are presented in table 3 before and after it. This is also shown in the figure 4 below.

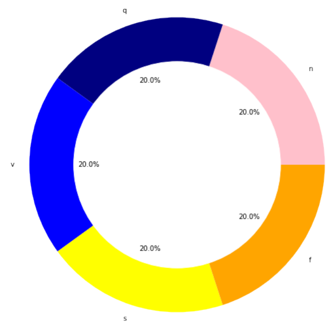

Figure 4. Architecture of the balance database (35).

Table 3. The training part of the MIT-BIH dataset of heartbeats before and after SMOTE.

Dataset	Classes	Classes before SMOTE	Classes after SMOTE
MIT -BIH Dataset	N	72471	57961
	S	2223	57961
	V	5788	57961
	F	641	57961
	Q	6431	57961

Machine Learning

Machine Learning (ML) has been successful in computer-aided diagnostics. ML is a developing computing subfield. It learns from its environment to mimic human intelligence. Since it requires pattern interpretation and data collection, it is used when these are not possible. Doctors use many MR methods to diagnose arrhythmia. ECG readings can predict difficult-to-diagnose medical conditions with machine learning algorithms. Machine learning to classify a data set usually uses this standard operating procedure. Several machine-learning classifiers exist in ML. SVM is a supervised machine learning technique for classifying problems into two groups that uses good classification methods. (24).

Support Vector Machine (SVM)

Boser, Guyon, and Vapnik invented SVM in 1992. Math-based and human-guided, it is a popular machine learning algorithm. It has been proposed to solve many medical, engineering, text classification, image segmentation, and pattern recognition issues. SVMs were first used for binary classification, where they find a decision boundary (called a ”hyperplane”) that divides data into two classes. SVMs with different kernels work well with large data sets like the ECG signal. Only a few kernel functions can classify biomedical signals. Because it distinguishes ECG signals well, the radial basis function (RBF) kernel SVM classifier has been widely used (7).

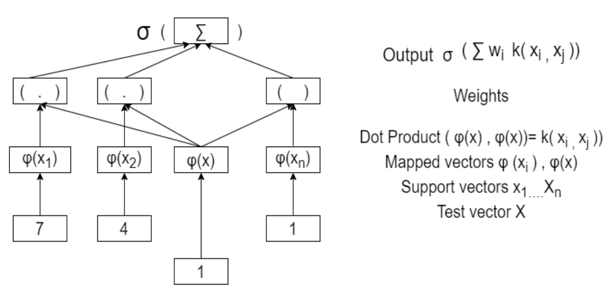

Figure 5. Architecture of SVM methods(7).

Figure 5 clearly illustrates SVM methods. where v and I represent kernel coefficients 1, 2,...

Non-linearly (via phi), the input x and the support vectors xi (points) are mapped into the feature space F, where the inner product is computed using the kernel k(•,•). In reality, these two layers are connected together. If you want to add straight line results, use quadratic programming or the eigenvalue problem V. The linear combination is in f(x). f(x) = sign of pattern recognition and regression estimation (x + b).

K-nearest neighbours (KNN)

Supervised machine learning, especially for classification tasks, is popular with the K-nearest neighbours (KNN) algorithm. However, it is a ”non-parametric lazy algorithm,” unlike the other methods, which fit training data differently. KNN does not train. Math groups things instead. The KNN sorts feature vectors by their closest training sample labels in the feature space. Calculate the distance (Hamming, Euclidean, Minkowski, etc.) between a feature vector or a new instance and all of the feature vectors in the training set to find the k-nearest neighbour. The class with the most votes is used to predict the unknown feature vector. Recent ECG classification studies have used the KNN (25). This can be seen in figure 6.

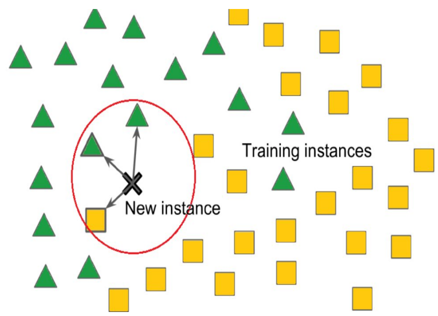

Figure 6. A simple flowchart for the k-nearest neighbor modeling (r33).

Random Forest (RF)

RF is an ensemble learning strategy that creates many individual DTs and uses a majority voting method to combine their predictions. RF can avoid deep DT overfitting because it uses a subset of the features used to make them. The number of estimators (trees) is crucial when training an RF model. This parameter was discovered using a grid search. 200 estimators were chosen. They used the default values for other RF model parameters (27). Figure 7 depicts this.

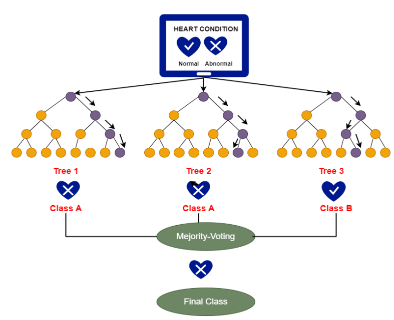

Figure 7. A simple diagram for the Random Forest modeling (27).

Deep Learning

Deep learning (DL) uses ”training data” to learn, predict, improve decisions, or find complex patterns. CNNs are more practical than traditional learning methods because you can usually improve their accuracy by increasing the network or training dataset. Decision trees and support vector machines (SVMs) require a lot of data and human input to be generalizable, making them unsuitable for many modern applications. Recently, deep learning (DL) architectures like Alex Net, VGG16, and ResNet-50 have been proposed to improve learning task accuracy (10)

Alex Net

An eight-layer convolutional neural network called AlexNet is a trained network stored in ImageNet. The trained network can classify photos into 1000 categories, including animals, keyboards, mice, and pencils. Thus, the network can represent many images using many features. Pictures sent to the network can only be 227 by 227. AlexNet's best feature is image direct-to-classification. Convolution layers automatically find image edges, and fully connected layers can learn them. More convolutional layers may simplify visual patterns (11). Figure 8 illustrates this.

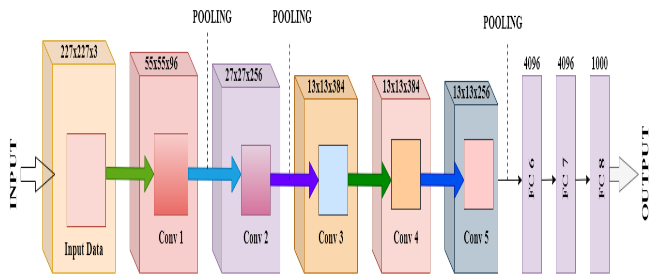

Figure 8. Architecture of the Alex Net model(11).

This study uses AlexNet, which is a deep CNN structure that has already been trained, instead of making its own. AlexNet is used to pull out the parts of an electrocardiogram automatically. The AlexNet architecture is made up of five layers that do convolution, three layers that do pooling, two layers that are fully connected, and one layer that does output. The AlexNet architecture is made up of five layers that do convolution, three layers that do pooling, two layers that are fully connected, and one layer that does output.

VGG-16

VGG-16 classifies things. It accurately classifies 1,000 photos into 1,000 categories at 92.7 percent. Transfer learning is simple with this method of grouping pictures. The VGG-16 Model, a 16-layer, fully connected CNN trained on the MIT-BIH dataset, classified ECG rhythms. Network models have convolutional, fully linked, and pooling layers (19).This is seen in figure 9.

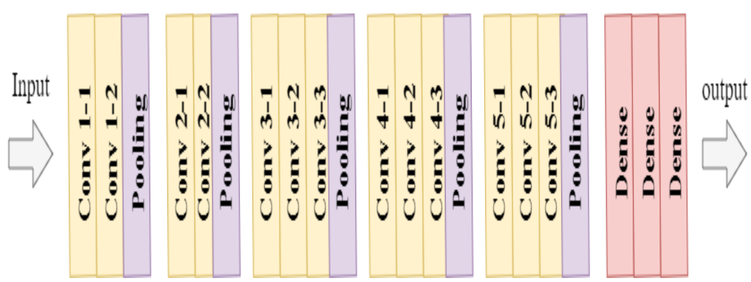

Figure 9. Architecture of the VGG-16 model(19).

In this work, we refer to the architecture of VGG16 as a convolutional neural network (CNN). It is considered one of the best vision model architectures ever created. The most interesting thing about VGG16 is that it doesn't use many hyperparameters and instead focuses on convolution layers for 3x3 filters with stride 1 and always uses the same padding and max pooling layers as 2x2 filters with stride 2.

ResNet-50

Resnet has a deep architecture with high accuracy and convergence. The framework adds a shortcut connection module to learn the residual and avoid deep network issues. Direct data sharing across the network makes it easier to find representative high-level features (46).

ResNet-50, which was used in this study, had 50 weighted layers. It used shortcut connections to add more convolutional layers to a CNN without causing gradients to go away. Some layers are ”jumped over” by a shortcut connection, leaving behind a residual network. The design of ResNet is based on two rules.

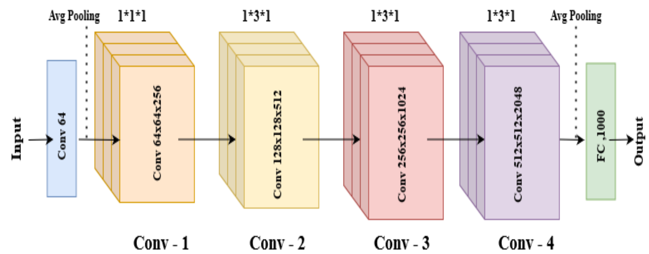

Figure 10. Architecture of the ResNet-50 model(46).

First, there are always the same number of filters in each layer, no matter how big the map is. Second, if you cut the size of the feature map in half, you need twice as many filters to keep the layer complexity the same. This is shown in above figure 10.

Dense Net

To classify heart rhythms automatically, we employed densely coupled convolutional networks (DenseNet) in this study. Each layer in a typical convolutional network is solely connected to the one below it. DenseNets, on the other hand, has direct connections between each layer and the layers that follow it. Each succeeding layer will now contain the feature maps from the previous layers. To achieve the same level of performance, fewer parameters are required than in traditional convolutional networks. The density structure and the proposed approach are depicted in Figures 11. Densely connected convolutional

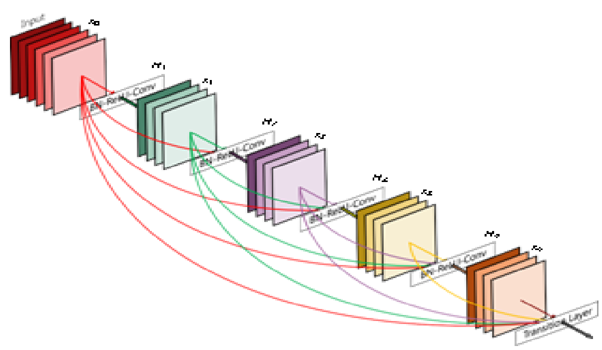

Figure 11. Architecture of the DenseNet(17).

networks (17), also called DenseNets, are the next step in making deep convolutional networks even deeper .We've seen how we've moved from Alexnet(11) , which had 8 layers, to VGG(19), which has 16, and ResNets (46), which have more than 100 and even more than 1000 levels.CNN gets into trouble when it goes further. This is because the path from the input layer to the output layer (and the other way around for the gradient) gets so long that the information and gradient can be lost before they reach the other side.DenseNets make it easier for layers to join to each other than in other architectures.When it comes to enhancing the information flow across layers, the Dense Block plays an essential role as a component of the DenseNet. It is made up of Batch Normalization(BN), rectified linear activation unit(ReLu), and convolution (conv).

Proposed Model

In this proposed model, we have first taken the data containing raw ECG signals from the MIT-BIH database. Then we filtered the signals with an IIR filter. The best of the filtered signals were preprocessed. In this preprocessing, we check whether there are any missing data or NAN values and add them to the data balance. Data balancing is a very important process because feeding the correct data to the ML or DL models will result in accurate results. For this, we used the Smote Technique. Thus, from the data balance, the balanced data is given to the data split to split it into training and testing. Later, we gave the split bata to the ML AND DL models for arrhythmia classification. A performance analysis was done to examine the results from all ML and DL models. Densenet has given good results in this area. We have included the proposed model that includes this entire process in the figure 12 below.

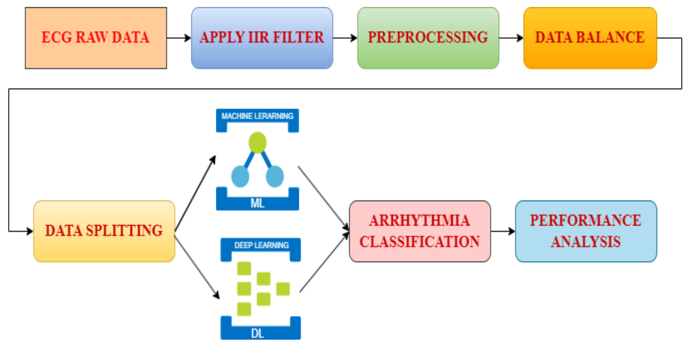

Figure 12. Architecture of the Proposed Model

IMPLIMENTED DIFFERENT MODELS RESULTS AND ANALYSIS

This section begins with performance evaluation measures. Following the machine learning findings, the deep learning outcomes are also presented in this section. Finally, the density results of the proposed technique are presented, along with comparisons to other network results.

Performance evaluation metrices

In every experiment, model training and evaluation are done with the help of the Python libraries scikit-learn and tensorflow. The SMOTE method was utilised in order to normalise the database. The performance of the proposed methodology is analysed and evaluated for each category of ECG signal. Calculating false positives FP, true positives TP, true negatives TN, and false negatives FN leads to the discovery of this value. Calculating sensitivity looks something like this:

$$Sensitivity(S_E) = \frac{T_P * 100}{(T_P + F_N)}$$

$$Specificity(S_P) = \frac{T_N * 100}{(T_N + F_P)}$$

$$Acuracy = \frac{(T_N + T_P) * 100}{T_N + F_P + T_P + F_N}$$

$$Precision(P) = \frac{TP * 100}{TP + FP}$$

$$F1score = 2 * \frac{(P * S_E)}{(P + S_E)}$$

Every machine learning pipeline has performance metrics. Every machine learning model, like linear regression and random forest, needs a way to measure how well it works. Just like performance metrics, every machine learning task can be broken down into either regression or classification. There are dozens of metrics for both problems, but we'll talk about the most common ones and what they tell us about how well a model works. Table 4 has the information in concern.

Table 4. MACHINE LEARNING METRIC PARAMETERS

Model	Best_Score	Best_Params
SVM	0.96	{'C':1 ,'KERNAL ':LINEAR}
LOGISTIC REGRESSION	0.90	{'N_ESTIMATORS': 5}
RANDOM FOREST	0.96	{'C':1}

Comparison of ML classification techniques

The main goal of this model is to determine whether the results obtained from SVM are better than those obtained from LR and RF models trained using all features simultaneously. For support vector machines (SVMs), product, summation, and majority rule are the three combined methods used. The following table shows the metrics and values for overall accuracy (ACC), average sensitivity, and accuracy. TThese values are presented in Table 5, and Figure 12 illustrates the bar graph representation of the data.

Table 5. Analysis of the differences and similarities between the findings produced by various ML classification methods.

ML Models	precision	recall	f1 score	Accuracy
SVM(Polynomial)	0.77	0.48	0.48	48%
SVM(Gaussian)	0.93	0.92	0.92	92%
SVM(Sigmoid)	0.95	0.96	0.96	96%
SVM(Linear)	0.95	0.96	0.96	96.5%
Logistic Regression	0.89	0.89	0.90	90%
Random Forest	0.95	0.96	0.96	96%

Comparison of Deep Learning Techniques

0.1.1 ALEX-NET Model

Additional details on the outcomes of AlexNet and this time frame may be seen in Figures 13, 14, and 15. This model achieved an accuracy of 96.37% and a loss value of 0.11.

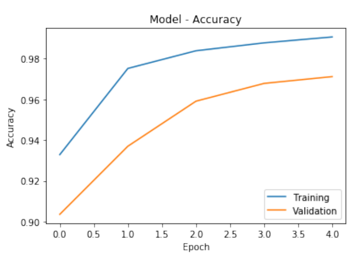

Figure 13. Dense Net Accuracy curve

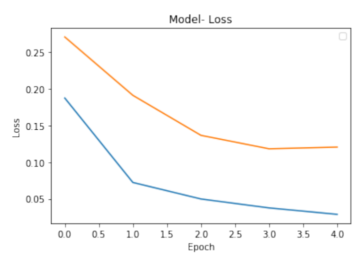

Figure 14. Dense Net Loss Curve

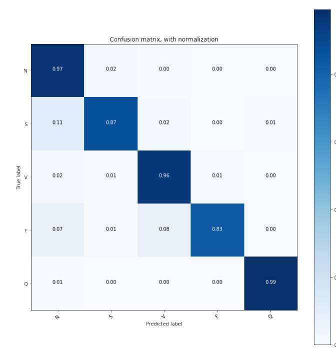

Figure 15. Dense Net Confusion matrix

VGG-16 Model

Figures 16, 17, and 18 depict the accuracy, loss curve, and confusion matrix of the VGG-16 Net. This model achieved a validation accuracy of 97% and an overall accuracy of 94%, with a loss value of 0.12.

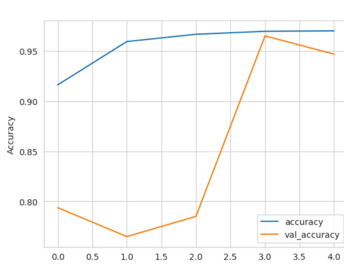

Figure 16. VGG-16 Net Accuracy curve

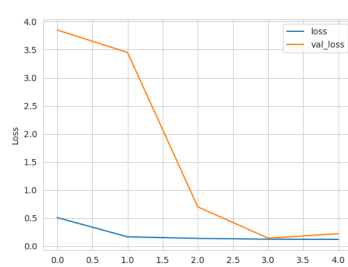

Figure 17. VGG-16 Net Loss Curve

Figure 18. VGG-16 Net Confusion matrix

RESNET-50 Model

Figures 19, 20, and 21 illustrate the accuracy, loss curve, and confusion matrix of the Resnet model. This model achieved an accuracy of 86% and a validation accuracy of 87.2%, with a loss value of 1.15.

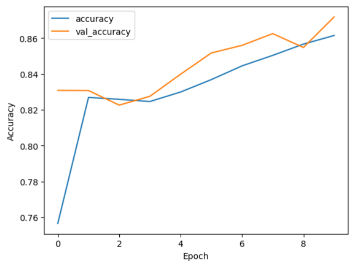

Figure 19. Res Net Accuracy curve

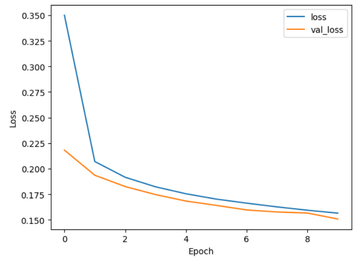

Figure 20. Res Net Loss Curve

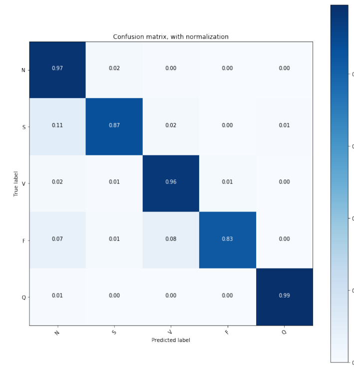

Figure 21. Res Net Confusion matrix

DenseNet-121 Model

Figures 22, 23, and 24 provide details of Densenet's accuracy, loss curve, and confusion matrix, respectively. The model achieved a validation accuracy of 98% and an overall accuracy of 99%, with a loss value of 0.2. Information about the total differences can be seen in the following table 6:

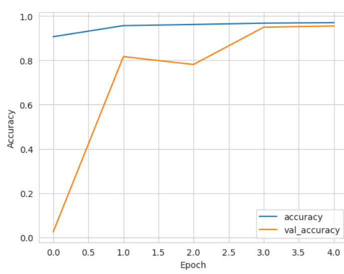

Figure 22. Alex Net Accuracy curve

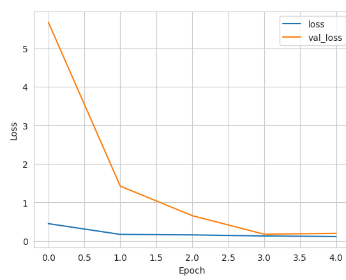

Figure 23. Alex Net Loss Curve

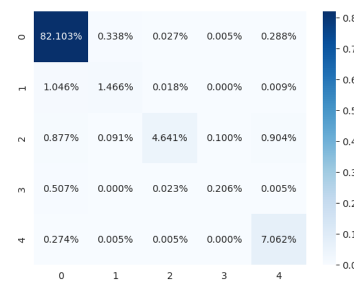

Figure 24. Alex Net Confusion matrix

Table 6. Analysis of the differences and similarities between the findings produced by various DL classification methods.

REF	TYPE OF TECHNIQUE	**ACCURACY**
(11)	AlexNet	96.37%
(19)	VGG-16 Net	94%
(46)	ResNet-50	87.2%
(17)	DenseNet-121	99%

THE PERFORMANCE DISCUSSION OF THE IIR FILTER IN COMPARISON TO FILTERS OF OTHER TYPES

In this study, we propose that applying a filter may provide completely distinct and more accurate results when classifying arrhythmias than would be possible without a filter. In this method, we used the IIR filter. The reason for the advantage of IIR filters over ordinary filters is that IIR filters generally require fewer coefficients to perform similar filtering operations, run faster, and require less memory space.

Let us examine those researchers who have used other filters, apart from the Infinite Impulse Response (IIR) filter, for the purpose of rhythmic categorization. A technique for the automated categorization of electrocardiograms (ECG) using a combination of several Support Vector Machines (SVMs) was suggested by V. Mondéjar-Guerra et al (28).The accuracy rate was 94.5% with high-frequency noise filtering. Mathews et al. (26) showed how the Restricted Boltzmann Machine (RBM) and deep belief networks (DBN) can be used in the real world to classify electrocardiograms (ECGs). They used a bandpass filter and achieved an accuracy of 75.5% in their classification work. Sandeep Raj et al. (31) introduced a novel approach for feature extraction by using the sparse representation methodology. This method effectively represents various electrocardiogram (ECG) signals using a band-pass filter, achieving an accuracy of 90.3%. Haoren Wang et al.(42) presented a dual, fully connected neural network model for accurate classification of heartbeats using a notch filter with an impressive accuracy rate of 93.4%. Felipe Meneguitti Dias et al. (9) suggested that single-lead ECG data could be used to classify arrhythmias with an accuracy of 88.6% by using the inter-patient paradigm and a band-pass filter. Using a band-stop filter and a deep neural network, Han Wu et al. (43) suggested a classifier with an accuracy of 91.9% for automatically identifying arrhythmias. The table 7 below contains every relevant piece of information related to these challenges.

Table 7. COMPARISON WITH THE EXISTING FILTER METHODS

REF	TYPE OF FILTER	**ACCURACY**
(28)	SVM with FIR Filter	94.5%
(26)	DBN with Band-Pass Filter	75.5%
(31)	CNN with Band-Pass filter	90.3%
(42)	CNN with Notch filter	93.4%
(9)	DNN with Band-Pass Filter	88.6%
(43)	DNN with Band-Stop Filter	91.9%

Based on these results, it appears that the suggested method is a reliable method of automatically categorising cardiac arrhythmia. By using established CNN architectures instead of building a deep CNN from scratch, it provides a reliable detection method. We found that the DenseNet 121 methodology gave the most accurate means of categorising arrhythmic beats after doing the aforementioned comparison. We have included the details of these in the table 8 and comparison of different filtering methods in figure 25 below.

Table 8. COMPARISON WITH THE PROPOSED FILTER METHODS

REF	TYPE OF FILTER	**ACCURACY**
(7)	SVM with IIR Filter	96.5%
(10)	RF with IIR Filter	96%
(11)	AlexNet with IIR Filter	96.37%
(19)	VGG-16 Net with IIR Filter	94%
(46)	ResNet-50 with IIR Filter	87.2%
(17)	DenseNet-121with IIR Filter	99%

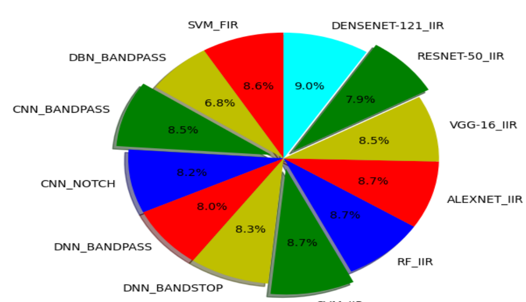

Figure 25. COMPARISON WITH DIFFERENT FILTER METHODS

CONCLUSION

In this work, we came up with a model called IIR filter method ,that uses machine learning and deep learning models to classify ECG arrhythmia using the MIT and BIH arrhythmia databases. During this process, the electrocardiogram will be transformed into grayscale images that are 128 pixels wide and 128 pixels high. Over 100,000 electrocardiogram beat images, including both normal and abnormal beats, are collected. The SVM, SMOTE, and CNN architectures are taken into consideration by the proposed model. This proposed method achieved 99 percentage accuracy. ECG arrhythmia classification results show that arrhythmia detection using ECG images and CNN models can help professionals diagnose heart disease based on ECG signals. The proposed algorithm for classifying ECG arrhythmia can be used in medical robots or scanners that analyse ECG signals and make it easier and more accurate for doctors to diagnose arrhythmia. We are designing an integrated ECG arrhythmia classification system that scans a patient's ECG monitor with a medical robot's camera and notifies the physician. ECG images from medical robotic cameras are classified by arrhythmia.

0.2 Feature Scope

We plan to deepen the network and see if the model can pick up features that are applicable to any ECG dataset, to see how far we can push this effort.

CONFLICT OF INTERESTS

There is no conflict of interests.

FUNDING

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