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Prediction and Classification of Normal ECG, Atrial flutter, Anteroseptal Infarct, Aortic Valve Cardiovascular Diseases from 12 Lead ECG Signals using Machine Learning and Deep Learning Techniques

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Cardiovascular disease (CVD) remains a leading cause of mortality and morbidity worldwide. Furthermore, it is projected that worldwide, cardiovascular disease is the primary cause of death and loss of disability-adjusted life years. Over time, wealthy countries have seen a decrease in the rates of cardiovascular death, while the burden of cardiovascular disease has significantly increased in low-income and middle-income countries. The main clinical method for identifying irregularities in cardiac function is through the utilization of a standard 12-lead electrocardiogram (ECG) apparatus. The general public can be screened and physicians can receive additional evaluations through automated 12-lead ECG machines. Nonetheless, a manual ECG interpretation necessitates both expertise and time. In today's rapidly changing world, accurate diagnoses of cardiac abnormalities are crucial for patients' well-being. This paper mainly focuses on the classification of Normal ECG, Atrial flutter, Anteroseptal infarct, and Aortic Valve cardiovascular diseases using Artificial Intelligence techniques. For this study, a dataset of 19140 ECG signals was extracted from the MIMIC-IV-ECG dataset. The original dataset contains more than 15 classes whereas for this study and the authors considered the following four classes namely Normal ECG, Atrial flutter, Anteroseptal infarct, and Aortic Valve. Each class identified represents the diagnosis of a particular set of ECG signals. Pre-processing was done on each ECG signal to prepare it for feature extraction using wavelet transform. A correlation matrix was used to select features after the feature extraction. Four algorithms namely "Random Forest (RF), K-Nearest Neighbour (KNN), Gradient Boosting (GB), and Artificial Neural Network (ANN)" have been compared on the dataset to analyze the performance. ANN scored better than the other models. The performance accuracy is RF - 93.15%, KNN = 91.90%, GB – 92.42%, and ANN – 94.50% respectively.

Keywords: Cardiovascular disease (CVD), Artificial Intelligence, Artificial Neural Network (ANN), ECG Signal, Normal ECG, Atrial flutter, Anteroseptal infarct, Aortic Valve.

1. Introduction

Cardiovascular abnormalities encompass a wide range of conditions that affect the heart and blood vessels. These abnormalities can vary in severity and can have a significant impact on an individual's overall health and well-being. It is essential to accurately detect and classify these abnormalities to provide appropriate treatment and interventions. One method for detecting and classifying cardiovascular abnormalities is through the use of electrocardiography. Electrocardiography is a non-invasive technique that records the electrical activity of the heart. This allows healthcare professionals to assess the heart's rhythm and identify any abnormalities.

In the field of medical diagnostics, electrocardiogram classification plays a vital role in identifying various cardiac abnormalities and conditions. Accurate classification of electrocardiogram signals is crucial for diagnosing and monitoring heart conditions. Traditional methods of ECG classification have relied on manual analysis and domain expertise, which can be subjective and time-consuming. With the advancements in deep learning techniques, there has been a growing interest in using these methods to classify ECG signals automatically and accurately. Deep learning models have shown promising results in various aspects of ECG classification and prediction [1].

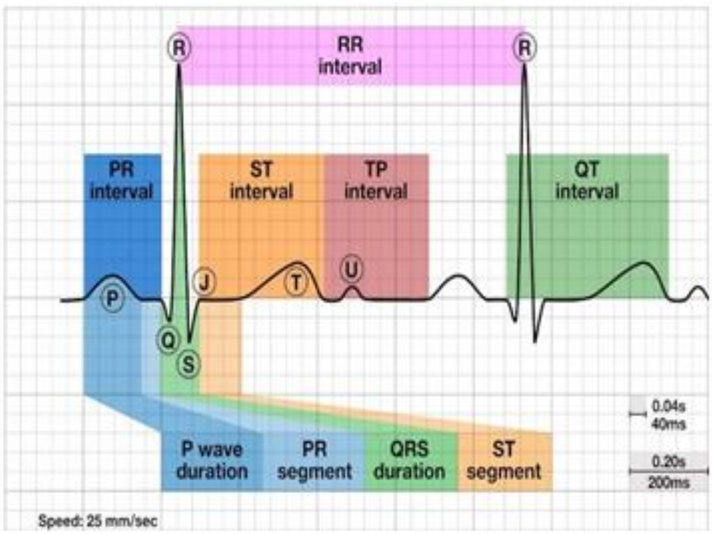

Fig. 1. ECG Signal [5]

Electrocardiography (ECG) is a widely used diagnostic tool that records the electrical activity of the heart, providing valuable insights into cardiac function. One of the key features of an electrocardiogram (ECG) is the presence of the PQRS waveform, which reflects the depolarization and repolarization processes within the heart. The P wave represents atrial depolarization, the QRS complex signifies ventricular depolarization, and the T wave corresponds to ventricular repolarization.

The analysis of the PQRS waveform can offer crucial information about the heart's health and reveal any underlying abnormalities [6][7]. For instance, changes in the morphology, duration, or timing of these waveforms can indicate various cardiac conditions, such as arrhythmias, conduction disorders, or myocardial ischemia [8].

Several studies have explored the techniques for ECG signal processing and analysis to improve the detection and classification of PQRS waveform abnormalities. One approach involves the use of wavelet transformation to remove noise and artifacts from the ECG signal, which can enhance the accuracy of T and P waves detection [6][9]. Another method focuses on recognizing and reducing interference on 12-lead electrocardiograms to ensure high-quality ECG recordings.

By leveraging advanced signal processing algorithms and robust feature extraction techniques, researchers have developed automated systems for the recognition of cardiovascular diseases based on the analysis of the PQRS waveform. These advancements have the potential to assist clinicians in the early diagnosis and management of cardiac conditions, ultimately improving patient outcomes [6][7][8][9].

Deep learning models can automatically learn informative feature representations from raw ECG data, eliminating the need for handcrafted features. These models can process the raw signal data and extract relevant features in an end-to-end manner, leading to improved performance in classifying different types of abnormalities such as normal ECG, atrial flutter, anteroseptal infarct, and aortic valve issues. Source: Recently, deep learning has been successfully implemented in various domains such as computer vision, natural language processing, and speech recognition [2]. With the application of deep learning techniques, researchers have explored different methods to automatically classify ECG signals.

These methods often involve the use of convolutional neural networks or recurrent neural networks or a combination of both. Deep learning techniques have the potential to revolutionize ECG classification by improving accuracy, efficiency, and the ability to handle large intra-class variations. By automatically extracting and learning features from ECG signals, deep learning models can enhance the diagnostic accuracy of cardiac diseases and reduce the possibility of an unexpected cardiac arrest [3].

The advantages of using deep learning algorithms in ECG classification are evident

Firstly, deep learning models can handle large amounts of data and learn from it, allowing them to capture complex patterns and relationships within the ECG signals. This enables them to accurately classify different types of abnormalities and improve diagnostic accuracy. Additionally, deep learning models can adapt and learn from new data, making them more robust and versatile compared to traditional methods. Furthermore, the end-to-end nature of deep learning approaches eliminates the need for manual feature extraction, reducing subjectivity and saving time. Moreover, deep learning algorithms have been shown to outperform traditional machine learning approaches in various studies. They have proven to perform better in terms of specificity, sensitivity, and classification accuracy. Therefore, the application of deep learning techniques in ECG classification holds great promise for improving the accuracy and efficiency of diagnosing cardiac abnormalities such as normal ECG, atrial flutter, anteroseptal infarct, and aortic valve issues [4]. By leveraging the power of deep learning techniques, such as convolutional neural networks and recurrent neural networks, researchers have been able to achieve remarkable results in automatically classifying ECG signals. The classification of normal ECG, atrial flutter, anteroseptal infarct, and aortic valve issues using deep learning techniques has the potential to provide accurate and timely diagnoses, enabling early intervention and improved patient outcomes. In conclusion, deep learning techniques have emerged as a promising approach for the classification of ECG signals [5].

They have the potential to revolutionize ECG classification by improving accuracy, efficiency, and the ability to handle large intra-class variations. The use of deep learning techniques in ECG classification, including the classification of normal ECG, atrial flutter, anteroseptal infarct, and aortic valve issues, has shown significant promise in improving diagnostic accuracy and efficiency [3]. It is crucial to remember that even though deep learning techniques show great potential, further research and validation are needed to ensure their reliability and effectiveness in real-world settings.

This research compares a DL algorithm with multiple ML algorithms using a labeled collection of ECG signals to categorize them into four groups: Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction. The MIMIC-IV v1.0 dataset was refined to create a dataset consisting of 19,140 ECGs. Each category within the dataset corresponds to the diagnosis of a specific group of ECG signals: Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction. Prior to extracting features, each ECG signal underwent pre-processing. Following feature extraction, features were chosen based on a correlation matrix. This study involves the comparison of four algorithms using the provided dataset.

In conclusion, the classification of Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction conditions using deep learning techniques has shown great promise in improving diagnostic accuracy and treatment outcomes for cardiovascular diseases. By leveraging the power of deep learning algorithms, this study has made significant advancements in the classification of Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction conditions based on ECG signals. These advancements have the potential to revolutionize the assessment and treatment of patients with valve disorders, since deep learning algorithms have the potential to replicate or replace the multimodal evaluation and decision-making process currently conducted by healthcare professionals, leading to more efficient and precise diagnosis and treatment plans. Four algorithms namely "Random Forest (RF), K-Nearest Neighbour (KNN), Gradient Boosting (GB), and Artificial Neural Network (ANN)" have been compared on the ECG signals to analyze the performance. ANN is better than the other models. The performance accuracy is RF – 92.7%, KNN = 83.8%, GB – 83.2%, and ANN – 93.5% respectively. In recent years, deep learning techniques have played a crucial role in the classification of Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction conditions, allowing for improved accuracy in the diagnosis and treatment.

2. Related Work

In our proposed study, the authors would like to predict and classify Normal ECG, Atrial Flutter, Anteroseptal Infarct, and Aortic Valve cardiovascular diseases from ECG signals. Some of the previous work is discussed here.

The purpose of the study by Bhatt et al. focuses on utilizing machine learning techniques for effective cardiovascular disease (CVD) prediction, crucial for accurate diagnosis and prognosis in clinical settings. Various models such as random forest, decision tree classifier, multilayer perceptron, and Xgboost were employed, with the multilayer perceptron demonstrating the highest accuracy of 87.28%. Feature selection methods and model comparison highlighted the importance of selecting appropriate algorithms to enhance prediction outcomes. Additionally, the study emphasizes the potential of machine learning in improving diagnostic accuracy and treatment planning for CVD patients, showcasing the significance of advanced algorithms in medical decision-making processes [10].

The research paper by Hassaballah et al. introduces an automatic arrhythmia classification approach for ECG heartbeat classification in smart healthcare systems, integrating metaheuristic optimization (MHO) with machine learning (ML) classifiers [2]. By optimizing the search parameters of classifiers like SVM, kNNs, GBDT, and RF, the proposed approach significantly enhances classification accuracy to 99.92% and sensitivity to 99.81%, outperforming existing methods through experiments on various databases [11].

The research paper by Ahmed explores Electrocardiogram (ECG) signal classification using deep learning methods like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. By investigating these techniques, the study aims to improve the accuracy and effectiveness of diagnosing various cardiac conditions through the analysis of ECG signals. The integration of CNN and LSTM models showcases a promising approach to enhancing ECG signal classification [12].

The study by Lee et al. developed an AI-enabled ECG model to detect obstructive coronary artery disease (CAD) using data from 4951 patients who underwent coronary angiography (CAG) [4]. The AI model, incorporating age, gender, and ECG data, showed comparable performance to traditional cardiovascular risk factors (CVRFs) with an AUC of 0.70 [4]. The model outperformed cardiologists in F1 score and was validated on an external cohort [4]. Combining ECG and CVRFs improved the AUC to 0.72, suggesting the model's potential as a clinical tool for identifying patients needing further diagnostic tests [13].

The study performed by Roy et al. investigates the use of deep learning and machine learning algorithms for detecting valvular heart diseases, achieving high accuracy with a modified Xception network model, which outperformed other models like LeNet-5, AlexNet, and VGG16 [5]. The study also found SVM and Random Forest to be the most effective among machine learning methods [14].

The paper by DİKER and AVCI focuses on the feature extraction and classification of Electrocardiogram (ECG) signals to diagnose heart disorders using a deep learning method. It employs a CNN for automatic feature extraction and an Extreme Learning Machine (ELM) for classification, attaining an accuracy of 88.33%, sensitivity of 89.47%, and specificity of 87.80%. The study uses the publicly available PTB Diagnostic ECG database and compares the ELM's performance with other classifiers like k-NN, SVM, and Decision Trees, demonstrating superior results with the ELM [15].

This study by Thilagavathy et al. details a robust approach for real-time ECG signal enquiry and organization, employing “Discrete Wavelet Transform and Support Vector Machine (SVM)”. The approach comprises ECG signal preprocessing, feature extraction, and beat classification, achieving an impressive average classification accuracy of 98.67% on the MIT-BIH arrhythmia database. By utilizing level 4 estimated factors with Daubechies (db2) filter, the SVM classifier successfully categorizes ECG beats into six heartbeat types, demonstrating significant potential for accurate ECG signal processing and classification [16].

Bhyri et al.'s study combines LabVIEW and wavelet transform to extract ECG features and diagnose diseases. For low resolution signals, a technique for R-peak detection using daubechies (db6) wavelet and Haar wavelet is devised. Important characteristics such as heart rate, ST segment, T-wave amplitude and length, Q-wave width, R-wave width, and frontal plane axis are extracted for heart disease diagnosis, addressing conditions like tachycardia, bradycardia, ventricular hypertrophy, and myocardial infarction. The study utilizes CSE ECG database and data from “S.G.G.S. Institute of Engineering and Technology” [17].

The study by Elias et al. focuses on utilizing deep learning techniques for electrocardiographic analysis to detect left-sided valvular heart disease. The study discusses the development of a deep learning model that demonstrates high performance in diagnosing a variety of left-sided valvular heart diseases, providing a promising approach for accurate and efficient disease detection. The model's effectiveness highlights the potential of artificial intelligence in improving cardiovascular disease diagnosis and patient care [18].

An approach by Sawano et al. a developed a deep learning-based artificial intelligence algorithm for diagnosing significant aortic regurgitation (AR) using electrocardiography (ECG). The dataset consisted of 29,859 paired ECG and echocardiography data, including 412 AR cases. A multi-input neural network model outperformed a 2D-CNN model, demonstrating a significantly greater area under the receiver operating characteristic curve. The system intensive on the QRS composite in leads I and a VL when detecting AR. This innovative approach shows promise for sensing AR using 12-lead ECG data [19].

The research paper by Kwon et al. focused on developing an artificial intelligence (AI) algorithm to detect mitral regurgitation (MR) using electrocardiography (ECG). The algorithm was trained and validated using a large dataset of ECGs from two hospitals, demonstrating high accuracy in detecting MR. By analyzing 12-lead and single-lead ECGs, the AI algorithm identified key ECG regions crucial for MR diagnosis, offering promising results for early detection and prevention of MR progression [20].

The work by Tabassum et al. focuses on predicting cardiac diseases through Electrocardiogram (ECG) analysis using support vector machine (SVM). With excellent individual accuracies ranging from 83.3% to 88%, ECG measures such as heart rate, QRS complex, PR interval, ST segment elevation, and ST interval are used to identify arrhythmias such “atrial fibrillation, sinus tachycardia, myocardial infarction, and apnea”. The proposed method relies on time domain features extracted from ECG signals to model and identify various heart conditions effectively [21].

The study by Kwon, Lee, et al. developed and validated a deep learning-based algorithm combining a multilayer perceptron (MLP) and convolutional neural network (CNN) to detect significant aortic stenosis (AS) using 12-lead and single-lead ECGs. The algorithm demonstrated high accuracy, with AUCs of 0.884 and 0.861 for internal and external validation, respectively. The T-wave axis, age, and QTc were identified as the most important variables, and the sensitivity map showed the algorithm focused on the T wave of the precordial lead [22].

The paper by Ramachandran et al. presents a hybrid model combining Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Fully Connected Layers (FCL) to classify electrocardiography (ECG) signals, particularly addressing the challenge of unbalanced datasets. Using data from the MIT-BIH arrhythmia record, the model achieved high accuracy and robustness in detecting ECG abnormalities, outperforming existing methods. The architecture includes three convolution blocks, batch normalization, and exponential linear units (ELUs) for consistent activation costs. The approach converts 1D ECG signals into 2D images to enhance feature extraction and classification accuracy [23].

In order to assist doctors in identifying individuals who might have gone undiagnosed with severe aortic stenosis (AS) and prioritizing these results for subsequent clinical assessment, Thomas et al.'s study proposes a Diagnostic Precision Algorithm. A deidentified dataset of 1,147,157 echocardiogram results from 35 universities served as the basis for the algorithm's development. Aortic valve area [AVA], jet velocity [JV], and mean pressure gradient [MPG] are the three standard Doppler indices that must be present, with at least one of them in the severe AS range (according to the AHA/ACC criteria) and a recorded assessment of the severity of AS.

A decision tree technique was utilized to create a Severe AS Index, which calculates the probability that a patient with comparable results would be diagnosed with severe AS, based on the division of the reports into training/validation and test datasets. When it came to determining the probability of a severe AS diagnosis and using that information to prioritize doctor follow-up for patients who might not yet have a serious diagnosis, the algorithm performed remarkably well [24].

Our work proposes a straightforward and efficient approach to extract characteristics from ECG data and compare them using three machine learning techniques and one deep learning algorithm. The literature study is utilised to categorise ECG signals into four distinct classes: Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction conditions. These classes are selected using the MIMIC-IV v1.0 dataset, which has not been extensively.

3. Materials and Methods

This particular section of the research paper is dedicated to the comprehensive discussion and elucidation of the processes involved in data collection, feature extraction, and the proposed method which forms the crux of the study. Subsequently, the process of feature extraction, which involves the identification and extraction of pertinent characteristics or attributes from the collected data, will be elaborated upon in a thorough manner. Moreover, the section will delve into the intricacies of the proposed method, outlining the theoretical framework, algorithms, and procedures proposed by the researchers as a novel approach to addressing the research problem at hand.

3.1 Data Collection

This study have used the MIMIC IV dataset obtained from the publicly available database pysionet.org. The dataset contains approximately 800000 electrocardiograms collected from 160000 patients. These ECG were of 12 Leads and 10 seconds of length. The dataset also came with a detailed measurement in the form of CSV file that contains subject_id, study_id, report 1 to report 8, rr_interval, qrs_axis and so on. From the dataset authors filtered report 0 and report 1 and then grouped together based on particular condition. For the study purpose from the above said dataset a subset was created with 19,140 ECGs.

Table 1. Dataset Summary

Feature	Description
Sample Population	9000 patients
Total Observations	19140 ECG signals
Patient_id	A subject identifier that is unique across every record in the MIMIC-IV database.
Trail_id	The study in which the diagnostic ECG is associated with can be determined by an identifier.
report_0 to report_8	An ECG machine-generated cardiology report in text format. There will be a varying number of report numbers, with potentially empty rows separating them.
rr_interval	It is the time interval between two successive R-waves, which are the prominent upward deflections in the ECG waveform. (msec)
p_onset	The point on the ECG where the P wave starts, marking the beginning of atrial depolarization.(msec)
p_end	The completion of the P wave in an ECG signal, marking the end of atrial depolarization. (msec)
qrs_onset	It marks the beginning of ventricular depolarization, which is the electrical activity that triggers the contraction of the ventricles in the heart. (msec)
qrs_end	The QRS end refers to the point in an electrocardiogram (ECG) waveform where the QRS complex transitions into the ST segment. (msec)
p_axis	The P axis is the mean electrical direction of atrial depolarization represented by the P wave on the ECG. (degrees)
qrs_axis	It refers to the net direction of the electrical activity of the heart during ventricular depolarization, specifically during the QRS complex. (-90 - +180 degrees)
t_axis	The T axis in ECG refers to the orientation of the electrical vector representing ventricular repolarization, specifically the T wave. (degrees)

After the selection process, the dataset contains approximately 9000 subjects and 19140 records. In the total 19140 records, 13398 were used for training and 5742 were used for testing. Each category within the dataset corresponds to the diagnosis of a specific group of ECG signals: Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction. The summary of the dataset is given in Table 1.

For better understanding of the dataset, the selected classes are visualized in figure 2.

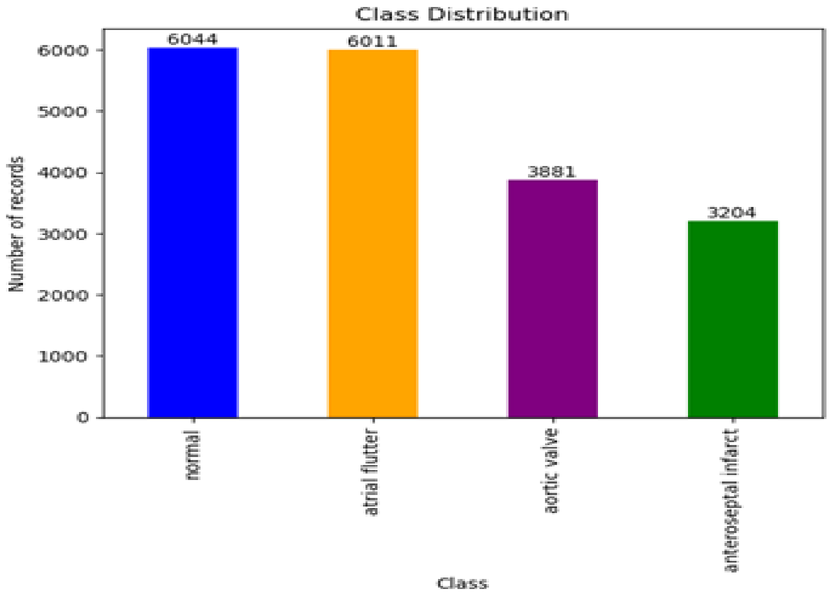

Fig. 2. Class Distribution

3.2 Data Preprocessing

3.2.1. Signal Filtering

Signal filtering is a fundamental method utilized in the realm of electrocardiogram (ECG) signal processing, playing a pivotal role in the precise detection and examination of cardiac activity. The ECG signals, which serve as representations of the heart's electrical activity, frequently encounter a myriad of noise and interference sources. These undesirable elements can occur from a variety of origins including power line disturbances, muscle contractions, baseline drift, and motion artifacts. It is paramount to implement effective signal filtering techniques to separate the genuine cardiac signal from these external disruptions, consequently amplifying the dependability and accuracy of subsequent diagnostic assessments. The process of signal filtering aims to enhance the quality of ECG data by eliminating unwanted noise and artifacts, thus facilitating a clearer interpretation of the underlying cardiac activity patterns. By employing advanced filtering algorithms and methodologies, researchers and healthcare professionals can optimize the analysis and interpretation of ECG signals, thereby improving diagnostic outcomes and patient care.

3.2.2. Baseline Wandering

The selection of the Daubechies wavelet (db4) for signal decomposition is crucial in signal processing applications. The db4 wavelet stands out for its exceptional suitability for analyzing biomedical signals, mainly attributed to its optimal balance between smoothness and localization properties. When decomposing an ECG signal, it is recommended to decompose it into distinct low-frequency and high-frequency components at multiple levels. This multi-level decomposition strategy proves to be highly effective in isolating the low-frequency baseline wandering component within the ECG signal. Following the decomposition process, it is essential to segregate the detail coefficients representing the high-frequency components from the approximation coefficients representing the low-frequency components. To further enhance the isolation of the low-frequency baseline wandering, it is common practice to nullify the detail coefficients at each level, thereby retaining only the approximation coefficients that effectively capture the baseline wander. The subsequent step involves signal reconstruction utilizing the modified coefficients, where the low-frequency approximation coefficients are preserved while the high-frequency details are eliminated.

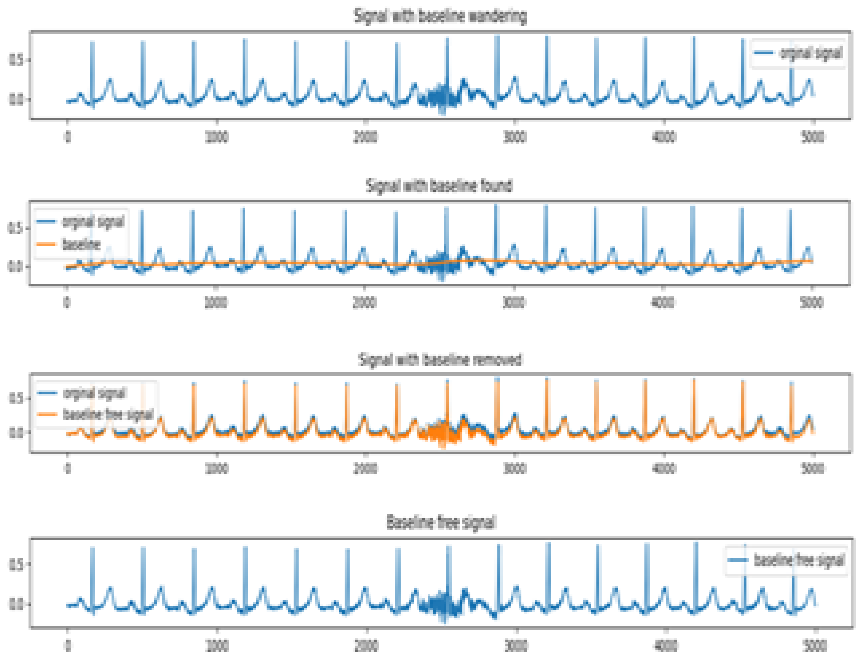

Fig. 3. Baseline Wandering Removal

This reconstruction procedure plays a pivotal role in restoring the baseline of the signal without the interference of high-frequency cardiac activities. By subtracting the reconstructed baseline from the original noisy ECG signal, the operation effectively eliminates the baseline wandering, thereby preserving the integrity of the high-frequency cardiac signal within the ECG data.

This comprehensive approach to signal processing not only aids in noise reduction but also ensures the accurate extraction of relevant physiological information embedded within biomedical signals. The utilization of advanced wavelet techniques, such as the Daubechies wavelet (db4), in signal decomposition processes showcases the significance of applying sophisticated mathematical methods in biomedical signal analysis. The process is shown in Fig. 3.

The db4 wavelet has specific filter coefficients h[k] and g[k]. These coefficients are derived from the wavelet's scaling and wavelet functions, and their formula is given in equation (1) and (2).

Low-pass filter coefficients h[k] for db4:

$$h[0] = \frac{1+\sqrt{3}}{4\sqrt{2}},\ h[1] = \frac{3+\sqrt{3}}{4\sqrt{2}}, h[2] = \frac{3-\sqrt{3}}{4\sqrt{2}},\ h[3] = \frac{1-\sqrt{3}}{4\sqrt{2}} \quad (1)$$

High-pass filter coefficients g[k] for db4:

$$g[0] = \frac{1-\sqrt{3}}{4\sqrt{2}},\ g[1] = \frac{-(3-\sqrt{3})}{4\sqrt{2}},\ g[2] = \frac{3+\sqrt{3}}{4\sqrt{2}},\ g[3] = \frac{-(1+\sqrt{3})}{4\sqrt{2}} \quad (2)$$

3.2.3. Noise Removal – High-Frequency

Determining the appropriate cut-off frequency represents a crucial stage within the realm of signal processing. In the realm of processing electrocardiogram (ECG) signals, it is common to select a cut-off frequency around the range of 40-50 Hz to efficiently eliminate high-frequency noise, a typical procedure in the domain. This procedure involves the creation of a low-pass filter, with Butterworth Filter Design. It distinguishes itself by maintaining a flat frequency response, rendering it a preferred choice across many applications due to its reliability and performance. The transfer function H(s) of an N-order Butterworth filter is given in equation (3).

$$H(s) = \frac{1}{\sqrt{1+\left(\frac{s}{\omega_c}\right)^{2N}}} \quad (3)$$

After determining the cut-off frequency, the subsequent step involves conducting wavelet decomposition on the ECG signal, a process that demands the selection of a suitable wavelet, such as the Daubechies wavelet, and the identification of the necessary level of decomposition essential for the analytical procedures. Following this stage, thresholding procedures are implemented to eliminate any traces of high-frequency noise present in the signal, with the decision on whether to employ soft or hard thresholding approaches contingent on the specific requirements of noise reduction dictated by the task at hand.

Following this, the developed low-pass filter is applied to the ECG signal to further bolster the noise reduction efforts. The wavelet decomposition phase is reiterated to ensure a comprehensive elimination of noise, underscoring the critical nature of selecting the appropriate wavelet type and decomposition level. Thresholding techniques are reintroduced to fine-tune the noise reduction process, with the selection between soft and hard thresholding strategies being tailored to match the unique noise characteristics exhibited by the signal.

The refined ECG signal, now stripped of high-frequency noise elements, is subject to optional smoothing through the utilization of a filter to address any residual noise artifacts that may persist. The role of visualization is paramount in the assessment process, with the filtered ECG signal graphed alongside the original signal to facilitate a comparative analysis of the efficacy of noise reduction techniques employed. In order to gauge the enhancement in signal quality in a quantitative manner, the signal-to-noise ratio (SNR) is computed, furnishing invaluable insights into the success of the noise reduction methodologies deployed.

Ultimately, the resultant output comprises the filtered ECG signal, now devoid of high-frequency noise, and deemed appropriate for subsequent analysis or diagnostic purposes. The methodical approach of selecting the cut-off frequency, crafting filters, conducting wavelet decomposition, applying thresholding, and assessing signal quality through SNR calculations ensures a thorough and robust methodology for noise reduction in ECG signal processing and is shown in Fig. 4.

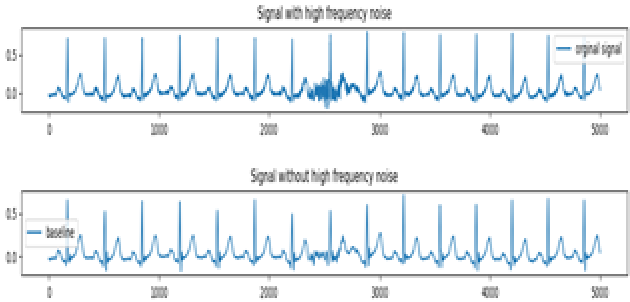

Fig. 4. Noise Removal – High-Frequency

3.2.4. Feature Extraction

Various characteristics can be derived from ECG signals across different domains, as evidenced in prior studies [9, 19, 23]. Key domains encompass time, frequency, time-frequency, and decomposition. This research focuses on time domain attributes, extracting 21 features from each ECG signal lead, resulting in a total of 252 features (21 features multiplied by 12 leads). The initial step involved the detection of R-peaks, serving as a reference for identifying Q and S waves. The QRS complex detection commonly employs Discrete Wavelet Transform (DWT). The current investigation utilizes the Haar wavelet for R-peak detection. R-peaks were identified by initially decomposing the signal by one level into low and high frequency components. The low frequency components approximate the original signal, while the high frequency components carry details on high frequency elements. Given the high-frequency nature of the R wave, emphasis was placed on the high-frequency component. To highlight the R wave's location, the high-frequency component was squared. Additionally, a threshold of 1.5 times the standard deviation of the signal was applied to filter out peaks exceeding the threshold amplitude. As the signal was decomposed by one level, the high-frequency signal became half the length of the original signal, necessitating upsampling by 2^1 to align with the original signal's scale, with 1 denoting the decomposition level utilized. With the signal obtained, the original R peak was detected as follows.

The act of distinguishing the ECG signal is carried out to accentuate the QRS complex. This process aids in bringing attention to the swift alterations within the signal, which are distinctive of the QRS complex as given in equation (4).

$$y(n) = x(n) - x(n-1) \qquad (4)$$

By squaring the differentiated signal, the peaks are further highlighted while smaller signal fluctuations are subdued. The same is achieved using equation (5).

$$y(n) = [x(n)]^2 \qquad (5)$$

The squared signal is then integrated over a dynamic window to produce a more even signal where the QRS complexes are more conspicuous. The identification of the R peaks within the identified QRS complexes involves locating the highest value within each detected QRS complex window by applying equation (6).

$$y(n) = \frac{1}{N}\sum_{i=0}^{N-1} x(n-i) \qquad (6)$$

The R peak is identified from the resultant signal with the following steps.

- A window consisting of 39 data samples is carefully chosen both before and after the estimated position of an R-peak in the signal under analysis.
- In this selected window, the precise positions of the lowest and highest amplitudes are identified through thorough examination.
- Furthermore, within this specific window, the position corresponding to the amplitude with the highest magnitude is pinpointed if its absolute value surpasses that of the amplitude with the lowest magnitude within the same window.
- Conversely, if the absolute value of the highest amplitude does not exceed that of the lowest amplitude within the window, then the location of the smallest amplitude is deemed more relevant and is thus selected.
- This critical process of detecting R peaks is elegantly illustrated in Figure 6, providing a visual aid to better understand the intricate steps involved in this crucial stage of signal processing.
- The deliberate selection of a 39-sample window before and after the approximate R-peak location is fundamental in ensuring accurate detection and analysis.
- Identifying the minimum and maximum amplitudes within this window is essential for subsequent computations and interpretations of the signal characteristics.
- The strategic choice between the location of the highest and lowest amplitudes based on their absolute values within the window significantly impacts the precision and reliability of R-peak detection algorithms.
- The visual representation of this detection process in Figure 5 serves as a valuable reference for researchers and practitioners in the field of signal processing, offering insights into the methodology and considerations involved in this critical stage.

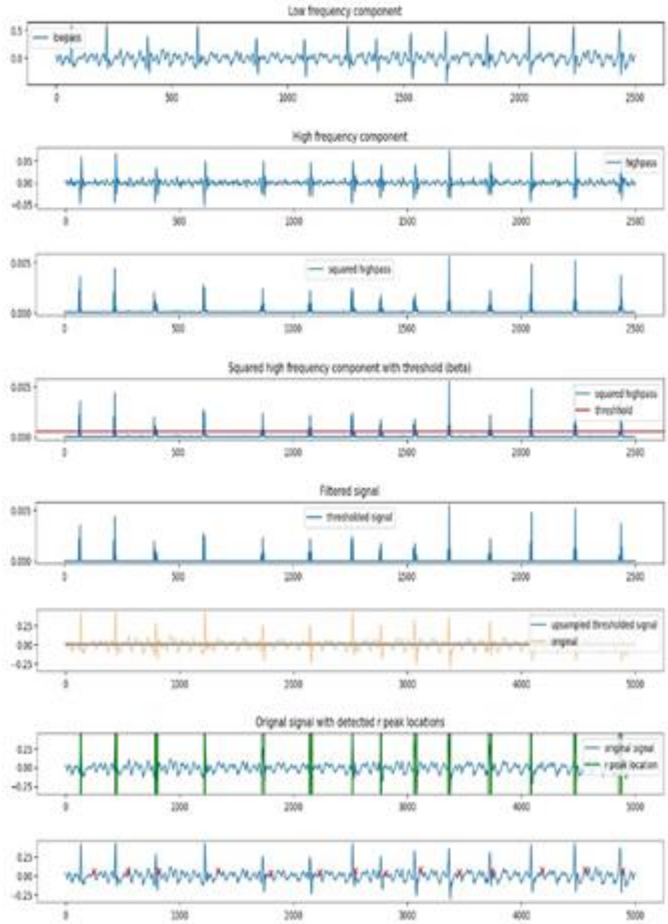

Fig. 5. R Peak Detection

After the identification of the R-peak positions in the signal, the process of locating the Q and S waves became straightforward and facilitated. In order to pinpoint these particular waves, a window of 39 samples is employed for analysis purposes. The identification of the Q-wave position entailed determining the position of the lowest amplitude within a window of 39 samples to the left of each R-wave location. Moreover, the localization of the S wave involved identifying the position of the smallest amplitude within a 39-sample window extending to the right from the R-wave location.

Subsequent to identifying the location of the Q wave, the task of pinpointing the P waves involved locating the maximum magnitude (or amplitude) within a 65-sample window to the left of the Q wave. Additionally, the determination of the T wave location was established by identifying the maximum amplitude within a range of 100 frames to the right of the S wave.

3.2.5 Feature Selection

The file containing machine measurements that accompanied the dataset included 9 ECG features, and these features were left unchanged in their original state. However, the rr_interval features were excluded from the pool of 252 features that were extracted because they were already present in the machine measurements file. In addition, a correlation matrix was formulated with the objective of identifying which features exhibit correlations among themselves. By defining a correlation threshold of 0.6, any pair of attributes demonstrating a correlation above 0.6 had one of them taken out, leading to a selection of 21 attributes. Afterwards, these 21 handpicked qualities were integrated with the initial 9 qualities, resulting in a grand total of 30 qualities in the dataset. This process ensured that only non-repetitive and uncorrelated features were considered for further analysis and modeling purposes.

4. Proposed Method

This research employs four distinct algorithms for modeling the selected characteristics, namely Random Forest (RF), K-Nearest Neighbours (KNN), Gradient Boosting (GB), and Artificial Neural Network (ANN).

In the conducted research, the Random Forest algorithm was utilized in the MIMIC IV dataset to process the initial machine measurement characteristics presented in a csv file format. Subsequently, the same algorithm was applied to the extracted features from the data. Both approaches exhibited discrepancies in terms of the training accuracy and the testing accuracy. To address this issue, the analysis involved the elimination of the rr interval derived from the ECG signals, as well as the exclusion of correlated features within the data signals. The ideal execution was seen when the overall number of estimators applied in the Random Forest model was altered to either 300 or 600. Notably, the Random Forest Classifier demonstrated a commendable accuracy rate of 93.15% when employing 300 estimators. This finding underscores the significance of parameter tuning and feature selection in enhancing the predictive capabilities of the Random Forest model. The results suggest that refining the input features and tuning the algorithm parameters are crucial steps in optimizing the performance of machine learning models like Random Forest. Furthermore, these results emphasize the role of preprocessing techniques in enhancing the overall efficiency and accuracy of predictive modeling algorithms.

The K-Nearest Neighbor method, a fundamental technique in machine learning rooted in supervised learning principles, operates on the premise of similarities between new and existing data points. By assigning new data to the category most akin to current ones, it leverages all available data for classification based on similarities. This method, known for its adaptability, is versatile for regression and classification tasks, though primarily used for classification challenges. As a non-parametric algorithm, the K-Nearest Neighbor does not assume any underlying data patterns. It is recognized as a diligent-learner as it retains information from the training set, acting on it at the classification stage. By preserving the dataset during training and categorizing new data based on similarity, this algorithm can effectively classify incoming data. The classification accuracy depends on the choice of the number of neighbors, such as in the case where the K Neighbors Classifier yields a score of 91.90% with 2 neighbors.

In this research, we investigated the utilization of the gradient boost algorithm in forecasting cardiovascular disease using the MIMIC IV dataset, an extensive electronic health record repository. The MIMIC IV dataset encompasses a vast array of data concerning patient characteristics, medical background, test results, and clinical consequences. Data preprocessing was conducted, involving the selection of pertinent attributes and handling missing data. Subsequently, the gradient boost algorithm underwent training on the refined dataset, and its efficacy was assessed through diverse metrics such as accuracy, precision, recall, and F1-score. The outcomes demonstrate that the gradient boost model achieves a prediction accuracy of 92.42%, alongside an area under the receiver operating characteristic curve of 96.6%. This investigation underscores the capacity of the gradient boost algorithm to precisely predict cardiovascular conditions like Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction.

The developed algorithm is an ANN comprising 8 layers, with a total of 7 hidden layers, including 6 dense layers and one dropout layer incorporated into its structure. The input shape of the algorithm is connected to the initial hidden layer within the network. The Rectified Linear Unit (ReLu) functions as the activation function for the 7 hidden layers, whereas the SoftMax function is employed as the activation function for the output layer. The model is compiled using categorical cross-entropy as the loss function, the Adammax activation function, and accuracy as the evaluation metric. Moreover, the model underwent training for 200 epochs, using a batch size of 16 instances. To enhance the training process, the model is equipped with both a model checkpoint and early stopping callbacks. The model checkpoint callback is responsible for saving the model's weights and biases whenever there is an enhancement in a specified model metric. Conversely, the early stopping callback continuously evaluates a specific metric and halts the training procedure if there is no improvement observed over a predefined number of epochs, also known as patience. A schematic representation of the model architecture is depicted in Figure 6.

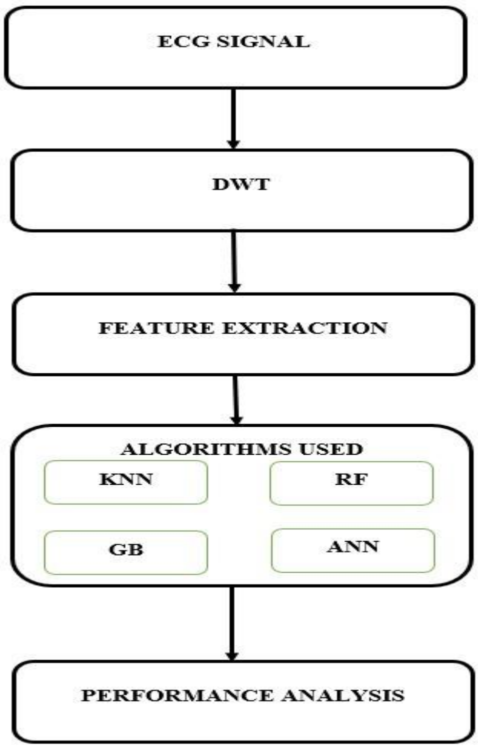

Fig. 6. Model Architecture

5. Results and Discussion

The model resulting from the application of each algorithm was employed in analyzing the test dataset. This process involved utilizing various evaluation metrics such as the "confusion matrix", "accuracy", "precision", "recall", "f1-score", and "AUC ROC" to assess the predicted labels of the test dataset. The confusion matrix is a vital tool that showcases the classification model's performance in a structured table format, regardless of whether it is a binary or multiclass classification issue. Furthermore, the confusion matrix serves as the cornerstone for deriving essential performance metrics like accuracy, f1-score, and precision. These metrics are pivotal in assessing the effectiveness and efficiency of the classification models under examination. Significantly, the confusion matrices for each of the four models established in this research endeavour are shown in Figure 7. The visual representation provided by the confusion matrices offers valuable insights into the classification performance of the models. Furthermore, the analysis of these matrices enables a comprehensive understanding of how well the models are able to classify the data points accurately. The evaluation of diverse metrics derived from the confusion matrices helps in ascertaining the strengths and limitations of the various models. Overall, the utilization of these evaluation techniques contributes to a thorough assessment of the classification algorithms' performance in handling the test dataset.

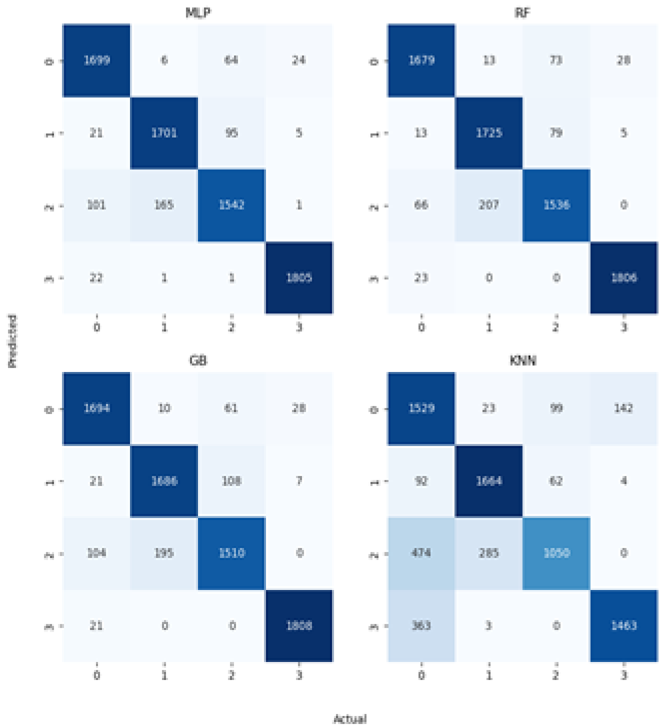

Fig. 7. Confusion Matrix ('Anteroseptal Infarction': 0, 'Aortic Valve': 1, 'Atrial Flutter': 2, 'Normal': 3)

The x-axis represents the classes that are actually observed, while the y-axis denotes the classes that are predicted by a model. Each cell within the matrix corresponds to a specific pair of predicted and actual classes, illustrating the frequency of instances where the prediction does not align with the ground truth. It is evident that the values present along the main diagonal indicate the number of instances where the predicted and actual classes match. By summing the values along this diagonal, the authors obtain the total count of accurately predicted records, whereas summing the remaining cells, excluding the diagonal, reveals the number of misclassifications.

For instance, considering the confusion matrix of an Artificial Neural Network (ANN), the cell (0, 0) signifies that 1699 instances were correctly predicted as Anteroseptal Infarction. Furthermore, cell (1, 0) highlights those 21 instances were erroneously classified as 'Anteroseptal Infarction' when they actually belong to the class 'Aortic Valve'. This analytical framework provides a comprehensive overview of the model's performance in differentiating between classes and offers insights into the nature of prediction errors that occur. The structured arrangement of the confusion matrix facilitates a detailed analysis of the model's capabilities and shortcomings in classifying data accurately. Understanding the distribution of predictions across various classes enables practitioners to fine-tune models and enhance their predictive accuracy for real-world applications. Evaluating the confusion matrix is crucial in assessing the effectiveness of classification algorithms and guiding improvements to optimize model performance for diverse datasets.

Remember or sensitivity, conversely, shows the proportion of accurate positive records among the total positive records based on a specified threshold. Precision, however, points to the percentage of true positive entries among the overall entries classified as positive based on a specific threshold. However, memory or reactivity indicates the fraction of correct positive instances within the total positive instances depending on a specified threshold. The F1-score, a metric that integrates precision and recall, offers a well-balanced evaluation of a model's performance. Moreover, the "Area Under the Curve (AUC)" of the "Receiver Operating Characteristic (ROC)" curve, commonly referred to as AUC ROC, is a significant metric in evaluating classification models. The ROC curve visually represents the trade-offs between True Positive Rate and False Positive Rate for varying threshold values, offering insights into model performance. An integral metric in evaluating classification models is the AUC ROC, which denotes the Area Under the Curve of the Receiver Operating Characteristic curve. The ROC curves for each model formulated in the investigation are delineated in Figure 8, exhibiting a visual juxtaposition of their performance in terms of true positive and false positive rates at various thresholds.

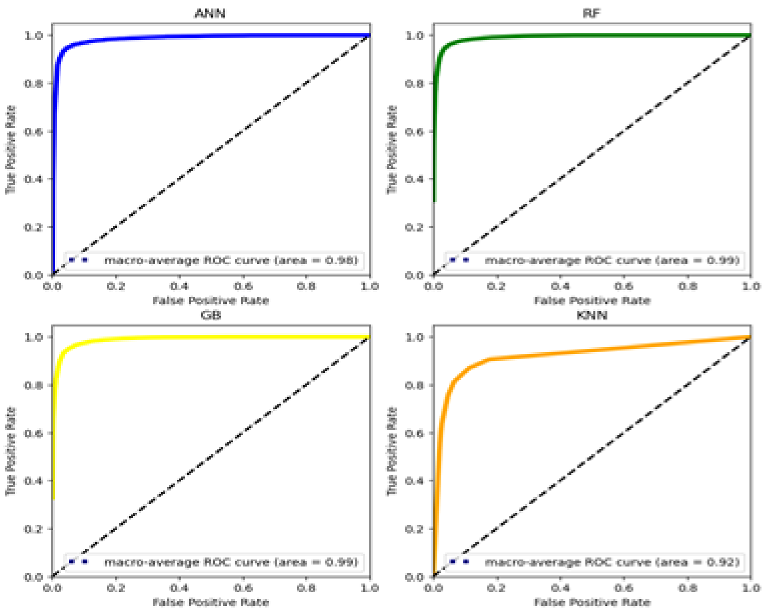

Fig. 8. ROC Curves

After an exhaustive review of the ROC curves showcased above, it is evident that both the Artificial Neural Network (ANN) and Random Forest (RF) models demonstrate curves that are positioned closest to the top-left corner of the graph in relation to the other models. After an in-depth evaluation of the ROC curves shown above, it is obvious that both the Artificial Neural Network (ANN) and Random Forest (RF) models showcase curves that are positioned closest to the top-left corner of the graph when contrasted with the other models. Furthermore, it is noteworthy that both the ANN and RF models boast an impressive AUC score of 0.99. This high AUC value signifies that these models excel in accurately identifying positive classes while effectively steering clear of false positive classifications. In essence, the proximity of the ROC curves to the top-left corner and the exceptional AUC values of 0.99 for both the ANN and RF models collectively indicate their superior performance in distinguishing positive classes with a minimal rate of false positives. Consequently, these findings underscore the robustness and reliability of the ANN and RF models in the context of classification tasks.

Table 2. Performance of the Models

Model/Metric	**Precision**	**Recall**	**F1 score**	**Accuracy (%)**	**AUC ROC**
ANN	93.6	93.5	94.23	94.50	98.7
RF	92.8	92.7	92.6	93.15	99.2
GB	92.12	92.42	92.15	92.42	96.6
KNN	86.4	91.90	91.20	91.90	94.5

The outcomes related to the performance metrics of each model are detailed in Table 2. Upon examination, it is apparent that the Artificial Neural Network (ANN) demonstrates a noteworthy accuracy rate of 94.5%, a precision score of 93.6%, a recall rate of 93.5%, an f1-score of 94.23%, and an outstanding Area Under the Receiver Operating Characteristic Curve (AUCROC) value of 98.7%. These statistics collectively indicate that ANN outperforms other conventional machine learning algorithms in the dataset under examination. Furthermore, a graphical representation in the form of a bar graph is displayed in Figure. 9 to visually illustrate the accuracy levels linked with each model under scrutiny. This visualization serves to aid in the comprehension of the relative performance of the models in a single view, thereby fostering a more intuitive understanding of their specific capabilities and limitations within the given dataset. In general, the precise numerical values and the visual representation collectively provide a thorough understanding of the effectiveness and strength of the different machine learning models utilized in the research, offering valuable insights for further analysis and decision-making processes in the realm of predictive modeling and data analysis.

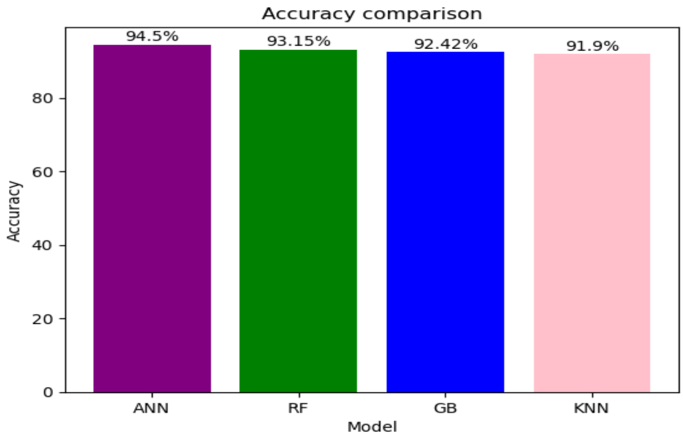

Fig. 9. Model Accuracy Comparison

6. Conclusion

The research has performed a comparative evaluation of the effectiveness of three machine learning (ML) algorithms, "Random Forest (RF)", "Gradient Boosting (GB)", and "k-Nearest Neighbors (KNN)", along with a deep learning (DL) algorithm, Artificial Neural Network (ANN), on a subset of the MIMIC-IV version 1.0 dataset, which includes four distinct categories: Normal, Atrial Flutter, Aortic Valve, and Anteroseptal Infarction. In addition, the examination has utilized wavelet transforms for the preprocessing of electrocardiogram (ECG) signals and the identification of R peaks, thus providing a basis for detecting other fundamental ECG features. Moreover, a straightforward and efficient approach has been utilized to identify the peaks of the remaining ECG waves. In conclusion, the recommended Artificial Neural Network (ANN) model has displayed superior performance over traditional Machine Learning (ML) algorithms, reaching an accuracy rate of 94.50% and an Area Under the Receiver Operating Characteristic curve (AUC ROC) of 98.7%. Moreover, the Random Forest (RF) algorithms have demonstrated notable outcomes with an accuracy of 93.15% and an AUC ROC of 99.2%. This inquiry marks an initial step in the categorization of normal, atrial flutter, aortic valve, and anteroseptal infarction within the MIMIC-IV v1.0 dataset. Prospective research endeavours aimed at enhancing model efficacy could involve the implementation of multi-input models that assimilate both the extracted features and raw ECG signals. Additionally, alternative forms of ECG signal representation could be incorporated into the multi-input model or assessed individually to evaluate the efficacy of diverse algorithms across the MIMIC-IV series of datasets.

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