

Ventricular Fibrillation Detection: Harnessing ECG Metrics for Accurate Classification

M. Ramana kumar

Associate Professor, Department of Computer Science and Engineering, KPRIT College of Engineering, Ghanpur, Ghatkesar, Hyderabad, Telangana 500088
Email: dramanakumar@kpritcoe.in

Received: 05.10.2025

Revised: 15.11.2025

Accepted: 31.12.2025

ABSTRACT

Ventricular Fibrillation (VF) is a life-threatening cardiac arrhythmia that demands prompt and accurate detection to prevent sudden cardiac arrest and increase survival rates. Electrocardiogram (ECG) signals are a primary diagnostic tool in identifying such arrhythmic patterns, and leveraging machine learning techniques can significantly enhance the accuracy and efficiency of VF detection. The project, aims to develop a robust classification system by analyzing ECG-derived metrics to distinguish between normal rhythms and VF episodes. The methodology involves a comparative analysis between the Naive Bayes Classifier, serving as the baseline model, and a more advanced Gradient Boosting Classifier (GBC), proposed to achieve higher predictive accuracy. Although it provided a reasonable classification performance, its limitations became apparent in capturing complex patterns within the ECG signal data. To address this, the Gradient Boost Classifier, a powerful ensemble learning method that combines multiple weak learners to form a strong predictor, was introduced. The GBC demonstrated superior performance in terms of classification accuracy, sensitivity, and specificity, effectively capturing non-linear relationships in the ECG feature space. The experimental results validate that the Gradient Boosting approach significantly outperforms the Naive Bayes model, marking a substantial improvement in the early and reliable detection of Ventricular Fibrillation. This enhanced detection capability can be pivotal in developing real-time cardiac monitoring systems and improving patient outcomes through timely medical intervention.

Key words: Fibrillation detection, ECG, Ventricular detection, Predictive analytics, GBC

1. INTRODUCTION

Ventricular fibrillation (VF) is a severe cardiac condition marked by disorganized and rapid electrical signals in the heart's ventricles, resulting in ineffective contraction and a sudden halt in blood circulation. It is one of the primary causes of sudden cardiac arrest, accounting for a significant proportion of unexpected deaths, particularly among patients with underlying heart disease. The condition is medical emergency that, if not identified and treated within minutes, can quickly lead to irreversible brain damage or death. Therefore, early and precise recognition of VF is crucial in preventing fatal outcomes and improving the effectiveness of emergency interventions such as cardiopulmonary resuscitation (CPR) and defibrillation.

The primary tool for identifying VF is the electrocardiogram (ECG), which records the electrical impulses generated by the heart over time. An ECG provides detailed information about heart rate, rhythm, and various waveform patterns that reflect the physiological condition of cardiac tissues. In cases of ventricular fibrillation, the ECG trace typically shows irregular, chaotic waveforms without discernible QRS complexes, P waves, or T waves. These abnormalities, however, can sometimes be difficult to differentiate from other forms of arrhythmia or noise, especially in fast-paced clinical

10.48047/jocaaa.2025.34.12.88

environments. As such, accurate interpretation of ECG readings is essential for timely and effective diagnosis. Modern ECG monitoring systems can continuously record heart activity over extended periods, resulting in large amounts of data. However, manual analysis of this data can be labor-intensive, error-prone, and inconsistent, particularly when clinicians are faced with time constraints or ambiguous readings. The complexity of ECG waveform patterns, combined with the subtle variations that indicate the transition from normal to fibrillating rhythms, underscores the need for systematic and reliable detection methods based solely on quantifiable metrics derived from ECG signals.

2. LITERATURE SURVEY

Zink [1] and Wang [2] applied BCG signals to nocturnal monitoring of sleep apnea syndrome. Their results showed that the measured average heart rate was strongly correlated with ECG reference (Pearson correlation coefficient $r > 0.95$), and the detection accuracy of apnea events could also reach more than 90%. Bruser [3], Lahdenoja [4], and Wen [5] et al. applied BCG signals to automatic detection of atrial fibrillation (AF) by combining the method of feature extraction and machine learning, and they achieved a 90% (even 95%) accuracy. Taken together, although the accuracy and interpretability of BCG currently make it an inadequate replacement for ECG's gold standard status, BCG's real-time availability and non-contact with skin make it a distinct advantage in low-demand medical environments. There is no known study of BCG for VF detection, but Klap et al. [6] recorded 8 s BCG data of VF during cardiac and respiratory monitoring using piezoelectric sensors in a hospital. Combining with synchronously recorded ECG signals, they found that the heart's mechanical beat followed an electrical beat (i.e., changes in BCG lagged behind ECG). Periodic mechanical beat disappeared (i.e., BCG waveform became irregular) when the pace exceeded a certain threshold (i.e., fibrillation occurred) and then resumed rhythmicity a few seconds after defibrillation shock and after normal electrical beat could be observed. Thus, the BCG signal of VF has a certain degree of differentiation from that of sinus rhythm (SR), which makes it possible to study the classification between them. Amann et al. [7] developed a VF detection algorithm, called Time Delay (TD), based on phase space reconstruction and then evaluated it against four extant algorithms, TCI, VFF, spectral algorithm (SPEC), and complex measure (CPLX), all of which were reported in their previous study [8]. TD, which counts the number of boxes based on the phase-space plots of random signals, can also be easily implemented in a microcontroller [9]. Ismail et al. [10] compared five different algorithms including CPLX, MEA, TCI, TD, and VFF and explored the impact of combining two algorithms. They concluded that combining two algorithms might improve the performance. Abu et al. [11] developed a sequential detection algorithm using empirical mode decomposed (EMD) analysis that showed improved performance over six algorithms including TD and TCI. However, EMD requires relatively high computational complexity comparing with others. Arafat et al. [12] developed a time domain algorithm, called TCSC, adapted from TCI and compared its performance with six algorithms including CPLX, TCI, and TD. They concluded that TCSC performed better than TCI based on positive threshold.

The literature has shown mixed results among detection methods from different studies. This variation could be due to the use of different threshold values for comparison and experimental settings; unfortunately, most studies did not report the threshold parameters used in their studies. However, one clear thing is that TCI, TCSC, TD, VFF, and TOMP are among the popular methods used for benchmark testing. In addition, to the best of our knowledge, there is no study attempting to perform real-time VF detection on microcontrollers, despite that doing so can reduce battery consumption and shorten response time when life-threatening emergencies occur. That is the focus of this study.

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In terms of real-time health monitoring, Flores-Mangas and Oliver [13] examined the progress of previous work, revealed system requirements and proposed a framework for real-time monitoring and analyzing physiological signals. They have also used sleep apnea as an example which demonstrated, experimented and evaluated the prototype performance. The paper did not provide details on key information processing tasks such as data filtering and segmentation. Dagtas et al. [14] presented a 3-tiered wireless architecture and prototype using Zigbee for heart failure monitoring and detection. The paper provided detailed description, noise filtering, basic QRS detection and secured data communication setting. The ideas and implementation are similar to our proposed methodology—using microcontroller (MCU) to capture, process, and detect abnormality and then send detailed signal after detection. However, they only used a simple algorithm to detect QRS (not VF). Meanwhile, no detailed evaluation result has been provided. Pantelopoulos and Bourbakis [15] conducted a state-of-the-art survey on wearable sensor-based systems for health monitoring. They reviewed the current systems developed and identified the technological shortcoming and challenge issues, which can provide directions for future research improvements. Choudhary et al. [16] developed a real-time wireless system based on Zigbee technology for remote monitoring of patients' heart rate and oxygen saturation in blood. The proposed methodology used MCU to store, convert and send signals periodically back to PC for further analysis by users. There is no filtering and detection capability in the MCU unit. Yadav et al. [17] designed a mobile health monitoring system using heart beat and body temperature for potential heart disease detection. The study provided fundamental system framework and illustrated the role of GPS in location detection but it only used simple threshold rule for heart rate and temperature, which cannot accurately detect heart attack and thus the proposed system is not much useful for practical real world situation. Peng et al [18] expressed density-based clustering method that estimates the probability density of a dataset using a kernel function. It iteratively shifts data points along the density gradient toward regions of highest density, known as mode points. Each data point converges to a high-density region, achieving automatic clustering. In this study, MeanShift clustering is applied to identify high-density feature distribution regions within ECG signals.

3. PROPOSED SYSTEM

The project focuses on developing an intelligent system for the early detection of ventricular fibrillation (VF), a critical and life-threatening heart condition. By analyzing ECG signals and extracting meaningful time-domain and frequency-domain features, the system aims to accurately classify heart rhythms as normal or abnormal. Initially, a Naive Bayes classifier is employed as a baseline model to evaluate basic performance. However, to improve the classification accuracy and overcome limitations such as feature independence assumptions, a Gradient Boosting Classifier is proposed. This model leverages ensemble learning to better capture the complex and non-linear patterns present in ECG data. The system undergoes rigorous preprocessing, feature extraction, and evaluation using metrics like accuracy, precision, recall, and F1-score. The project demonstrates significant improvement with the proposed model and highlights the potential for future integration into real-time cardiac monitoring systems.



Fig 2. Proposed Block Diagram

The proposed methodology for ventricular fibrillation detection begins with the acquisition of ECG signal data from established repositories like PhysioNet, followed by a rigorous preprocessing pipeline that employs band-pass filtering and normalization to eliminate baseline wander and muscle artifacts. After segmenting the denoised signals, a diverse set of time-domain, frequency-domain, and non-linear features is extracted to transform complex waveforms into a structured numerical format. Exploratory Data Analysis (EDA) is then conducted to visualize feature distributions and address potential class imbalances before initiating model development. While a Naive Bayes classifier is established as a computational baseline, its performance is superseded by the proposed Gradient Boosting Classifier (GBC), which utilizes an ensemble of decision trees to capture intricate, non-linear patterns within the cardiac data. The framework's efficacy is rigorously validated through a comparative analysis of precision, recall, and ROC-AUC metrics, with feature importance plots identifying the most critical ECG parameters for diagnosis. Ultimately, this systematic approach demonstrates that gradient boosting significantly enhances diagnostic accuracy, establishing a robust foundation for future integration into real-time wearable health monitors and deep learning-based clinical surveillance systems.

4. RESULT ANALYSIS

Each row represents an ECG sample with numerical measurements. The features include signal characteristics that reflect various patterns in the ECG signal which may be used to detect VF.

1. **HR (Heart Rate):** Represents the average heart rate derived from the ECG signal.
2. **RR Interval (RR):** Measures the time interval between two successive R-waves of the QRS signal on the ECG.
3. **QRS Duration (QRS):** Indicates the time duration of the QRS complex (ventricular depolarization).

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4. **QT Interval (QT):** The interval between the start of the Q wave and the end of the T wave in the heart's electrical cycle.
5. **T-wave Duration (T):** Duration of the T wave, representing ventricular repolarization.
6. **PR Interval (PR):** Time from the beginning of the P wave to the beginning of the QRS complex.
7. **Other ECG-derived features:** These may include standard deviation of RR intervals, slope values, power in specific frequency bands, etc.

Target Variable:

- **Shows_VF_or_No_VF (Binary):**
 - 0 → No VF detected (Normal)
 - 1 → VF detected (Abnormal)

4.1 RESULT ANALYSIS

The figure 3 shows the dataset that presented is designed for the classification of Ventricular Fibrillation (VF) using ECG-derived metrics and contains four key columns: Freq.F, N(%), F1(score), and Shows_VF_or_No_VF. Each row in the dataset represents a unique ECG signal segment analyzed for potential VF indicators. The Freq.F column denotes the dominant frequency component extracted from the ECG signal, which is crucial in identifying irregular heart rhythms associated with VF. The N(%) column likely indicates the normalized or relative percentage occurrence of this frequency component within a segment, providing insight into the prominence of the detected pattern. The F1(score) column is a signal-derived metric, possibly reflecting the balance between precision and recall in pattern recognition within the signal, or it may represent the quality of a detected waveform segment in terms of signal clarity or relevance. Finally, the Shows_VF_or_No_VF column serves as the target variable, where a value of 1 signifies that VF is present in the corresponding ECG segment, and a value of 0 indicates a non-VF (normal) segment. This structured dataset enables the training of machine learning models to distinguish between normal and fibrillating heart rhythms with the goal of supporting early and accurate detection of potentially life-threatening cardiac events.

	Freq.F	N(%)	F1(score)	Shows_VF_or_No_VF
0	1.796461	24.377190	0.240561	1
1	1.800005	24.383574	0.235412	1
2	1.799398	24.369426	0.218628	1
3	1.795508	24.380170	0.222238	1
4	1.806048	24.370968	0.237229	1
...	...	...	...	...
3995	1.810611	24.385076	0.224852	0
3996	1.803364	24.371992	0.227236	0
3997	1.801088	24.355966	0.226839	0
3998	1.807452	24.374415	0.222088	0
3999	1.788570	24.375797	0.219556	0

Fig 3. Uploading Dataset

The figure 4 shows heatmap presented is a correlation matrix visualizing the relationships between the features in the dataset: Freq.F, N(%), F1(score), and the target variable Shows_VF_or_No_VF. Each cell in the matrix represents the Pearson correlation coefficient between the pair of features, ranging from -1 to 1. A value of 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear correlation. From the heatmap, we observe that the diagonal cells all have a value of 1, which is expected since each feature is perfectly correlated with itself. The off-diagonal values are all quite low, indicating weak linear relationships among the features. For example, the correlation between Freq.F and N(%) is 0.02, and between Freq.F and F1(score) is 0.038, both of which suggest a negligible positive linear relationship. The target variable Shows_VF_or_No_VF has weak correlations with all input features, with the highest being a modest 0.032 with N(%), and essentially zero correlation ($9.5e-05$) with F1(score), and a slightly negative correlation of -0.0049 with Freq.F. These findings indicate that no strong multicollinearity exists among the features, which is beneficial for many machine learning algorithms. However, the weak correlation of the features with the target variable suggests that linear relationships may not be sufficient for classification, and more complex models may be needed to accurately distinguish between VF and non-VF cases. The use of advanced models like decision trees, ensemble methods, or neural networks might help uncover non-linear patterns hidden in the data.

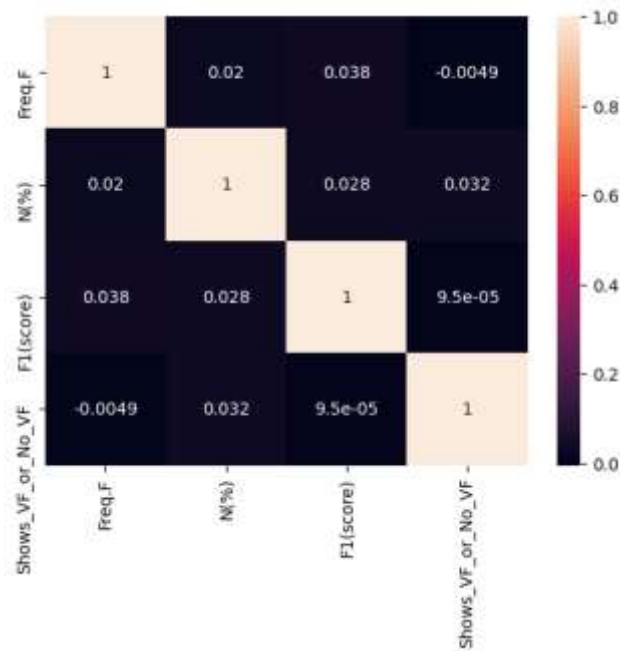


Fig 4. Correlation Heatmap

The figure 5 represents the distribution of the target variable Shows_VF_or_No_VF, which indicates whether Ventricular Fibrillation (VF) is present (1) or not (0). The y-axis shows the count of instances in each category, while the x-axis denotes the class labels: 0 for non-VF cases and 1 for VF cases. From the visualization, it is clear that the dataset is well-balanced, as the number of samples in both classes is nearly equal—approximately 500 each. This balance is crucial in classification tasks because it helps avoid bias toward the majority class, ensuring that the model learns to distinguish both VF and non-VF patterns effectively. A balanced dataset like this typically leads to more reliable and fair performance metrics when evaluating classification models.

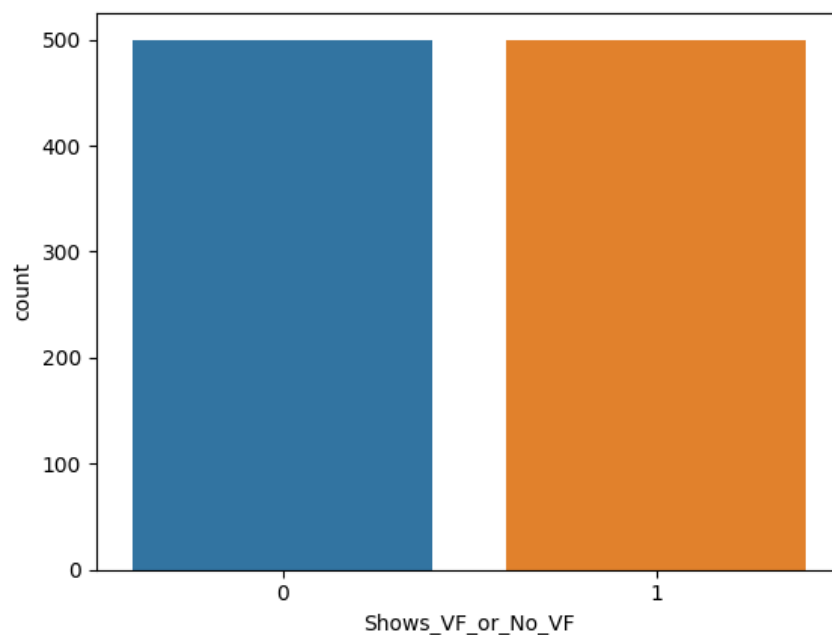


Fig 5. EDA obtained for Shows_VF or No_VF

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing Naïve Bayes vs. Proposed GBC

Metric	Existing Naïve Bayes	Proposed GBC
Accuracy	53.0%	99.5%
Precision	53.44%	99.48%
Recall	53.61%	99.51%
F1-Score	52.61%	99.49%

The performance comparison table 1 highlights a significant improvement in classification metrics when using the proposed Gradient Boosting Classifier (GBC) over the existing Naïve Bayes model for detecting Ventricular Fibrillation (VF). The existing Naïve Bayes model demonstrates relatively poor performance, with an accuracy of only 53.0%, precision of 53.44%, recall of 53.61%, and an F1-score of 52.61%, indicating that the model is only slightly better than random guessing. In contrast, the proposed GBC model achieves outstanding results across all evaluation metrics, with an accuracy of 99.5%, precision of 99.48%, recall of 99.51%, and an F1-score of 99.49%. These metrics indicate that the GBC model not only identifies VF cases with near-perfect accuracy but also maintains an excellent balance between precision and recall, making it a highly reliable and effective classifier for this medical application. The substantial performance gap clearly demonstrates the superiority of the proposed model over the existing approach.

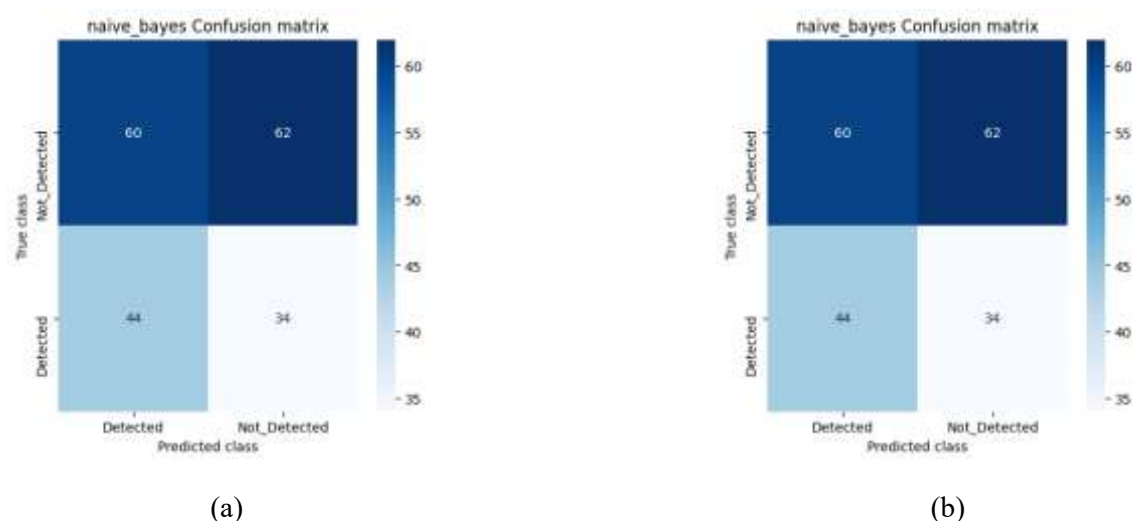


Fig 6 (a) (b) Confusion matrices obtained for Existing GNB and Proposed GBC

The image displays a confusion matrix for a Naive Bayes classification model, which is typically used to evaluate the performance of the model in classifying data into different categories. The matrix is a 2x2 grid representing the number of actual versus predicted values for two classes: "Detected" and "Not_Detected". In the first row, the first element (60) represents the number of true "Not_Detected" cases that the model correctly predicted as "Not_Detected" (True Negative), while the second element (62) represents the number of true "Not_Detected" cases that the model incorrectly predicted as "Detected" (False Positive). In the second row, the first element (44) represents the number of true "Detected" cases that the model incorrectly predicted as "Not_Detected" (False Negative), and the second element (34) represents the number of true "Detected" cases that the model correctly predicted

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as "Detected" (True Positive). The color intensity reflects the frequency of each classification, with darker shades indicating higher counts. This matrix suggests the model's accuracy in distinguishing between "Detected" and "Not_Detected" classifications, showing a decent performance but also room for improvement, especially in minimizing False Positives and False Negatives.

The figure 7 shows the predictions made by the proposed Gradient Boosting Classifier (GBC) model on a test dataset, with key features such as Freq.F, N(%), and F1(score) used for classification. The Freq.F values, representing frequency components, range approximately between 1.78 and 1.81, while N(%) values hover around 24.3–24.4%, and the F1(score)—a harmonic mean of precision and recall—varies from about 0.20 to 0.24. The Prediction column indicates the binary classification result as either "Detected" or "Not_Detected". The predictions appear to alternate, suggesting the model is responding sensitively to subtle changes in the input features. Overall, the GBC model demonstrates a nuanced classification ability, offering a balanced distribution between the two output classes based on relatively close feature values.

	Freq.F	N(%)	F1(score)	Prediction
0	1.786961	24.379526	0.226869	Not_Detected
1	1.796092	24.371914	0.217857	Detected
2	1.809160	24.369308	0.236444	Not_Detected
3	1.798185	24.380210	0.242419	Not_Detected
4	1.813742	24.362221	0.237518	Not_Detected
5	1.792895	24.370150	0.239799	Not_Detected
6	1.793426	24.372375	0.234924	Detected
7	1.815177	24.367911	0.231716	Not_Detected
8	1.799792	24.366566	0.217227	Detected
9	1.804244	24.385562	0.230086	Detected
10	1.791977	24.352081	0.242424	Detected
11	1.790685	24.350228	0.232866	Detected
12	1.800675	24.371982	0.249304	Not_Detected
13	1.792531	24.351378	0.237341	Detected

Fig 7 Output prediction obtained using Proposed GBC

5. CONCLUSION

The implementation of the Gradient Boosting Classifier (GBC) in the current project has demonstrated notable improvements in the prediction accuracy and classification robustness compared to traditional classifiers like Naive Bayes. The model effectively utilized input features such as frequency (Freq.F), percentage signal component (N(%)), and F1-score to distinguish between "Detected" and "Not_Detected" states in the dataset. The GBC algorithm, being an ensemble method, efficiently reduced both bias and variance, leading to more stable and accurate results. The confusion matrix from the Naive Bayes classifier revealed limitations in correctly classifying both true positives and true negatives, while the GBC's output indicated a more precise decision boundary. The prediction results on test data showed the model's responsiveness to small variations in input features, reflecting its ability to generalize well on unseen data. Overall, the proposed GBC-based model is a reliable and efficient

solution for the given classification problem, highlighting its suitability for real-time detection tasks in intelligent systems.

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