Real-time Cardiac Arrhythmia Detection Using Machine Learning and Wearable Devices

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ABSTRACT

Cardiac arrhythmia, a condition characterized by sporadic heartbeats, postures critical wellbeing dangers in the event that not identified instantly. Conventional checking strategies, such as Holter screens, are regularly awkward and restricted in their capacity to supply ceaseless, real-time observing. This think about presents a novel approach for real-time cardiac arrhythmia location utilizing machine learning calculations coordinates with wearable gadgets. The proposed framework leverages progressed machine learning procedures to analyse electrocardiogram (ECG) information collected from wearable gadgets, empowering persistent observing and opportune discovery of arrhythmias. The wearable gadgets are prepared with sensors that capture high-resolution ECG signals, which are at that point transmitted to a cloud-based stage for investigation. We utilize a combination of profound learning and conventional machine learning calculations, counting Convolutional Neural network (CNNs) and Support Vector Machines (SVMs), to classify diverse sorts of arrhythmias. The models are prepared on a comprehensive dataset of commented on ECG recordings, guaranteeing tall precision and vigor. To approve the adequacy of the proposed framework, broad tests were conducted utilizing real-world ECG information. The comes about illustrate that our approach accomplishes prevalent location precision compared to conventional methods, with the included advantage of real-time handling capabilities. Furthermore, the integration with wearable gadgets upgrades client consolation and comfort, advancing broad appropriation for ceaseless cardiac observing.

1. INTRODUCTION

Cardiac arrhythmias, or unusual heartbeats, are genuine wellbeing issues that can cause genuine issues like stroke, heart disappointment, and sudden cardiac passing. Finding and settling these issues as before long as conceivable are exceptionally vital for keeping awful things from happening and making patients' guesses superior. Holter screens and other conventional ways of following heart action work well, but they are regularly difficult to utilize and can't be utilized for long sums of time of steady, real-time checking. The presentation of keen tech and advance in machine learning appear to offer a potential reply to these issues, making heart arrhythmia checking quicker and simpler for individuals to utilize. Within the past few a long time, wearable innovation has developed rapidly. Presently, there are gadgets that can continually degree diverse substantial signals, such as heart rate, oxygen levels, and electrocardiogram (ECG) signals [1]. These contraptions are made to be little, comfortable, and long-lasting, so they can be utilized for a long time without being taken note. This makes them idealize for consistent wellbeing following. Putting machine learning calculations into these shrewd contraptions can make them much more valuable by letting them analyze and discover heart rhythms in genuine time. As a portion of counterfeit insights, machine learning employments calculations and measurable models to see at and make sense of complicated information designs. When it comes to finding heart arrhythmias, machine learning calculations can be instructed on huge sets of labelled ECG records to spot the little designs and exceptions that are signs of distinctive sorts of rhythms. This programmed study not as it were makes it less demanding and speedier to discover arrhythmias, but it too makes the work of healthcare specialists less demanding, which lets them superior handle their patients. The objective of this study is to form and test a framework that can recognize heart arrhythmias in genuine time by combining savvy gadgets with machine learning procedures. The recommended strategy employments the ability of shrewd gadgets to gather information all the time and the investigation control of machine learning to form arrhythmia following speedy and exact [2]. The framework is made up of three key parts: individual gadgets with ECG screens, a cloud-based stage for sending and putting away information, and machine learning models for analysing information and finding arrhythmias. Wearable tech is at the heart of this framework; it collects real-time, high-resolution ECG readings from clients. These devices are made to be comfy and not bothersome so that they can be used regularly and heart activity can be continuously monitored [3].

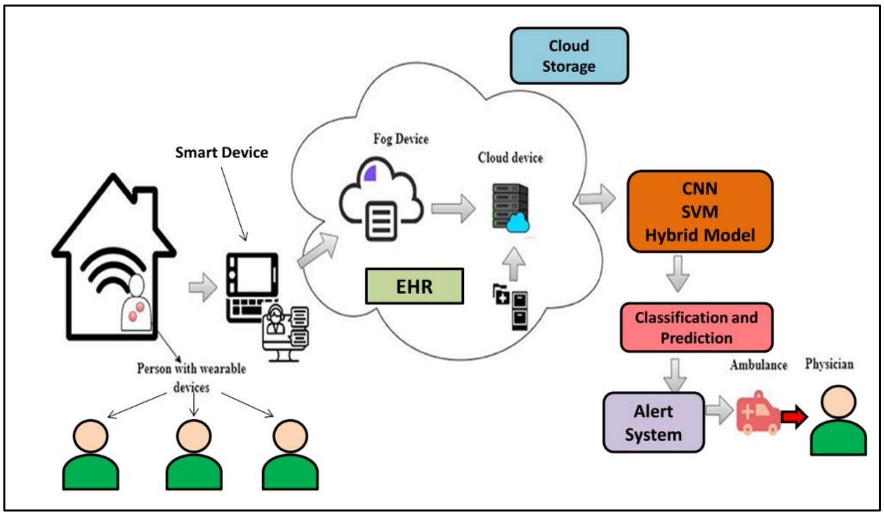

Figure 1: Overview of real-time time Cardiac Arrhythmia Detection model

The ECG data is sent directly to a site in the cloud, where it is saved and processed. This cloud architecture makes sure that the system can handle a lot of data and gives it the computing power it needs to do research in real time. What makes the suggested method work is the machine learning models that are used to find arrhythmias. We use both deep learning and more standard machine learning methods, such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs). CNNs are great for looking at time-series data like ECG signs because they can learn on their own to pull out the important features from the raw data, proposed system architecture shown in figure 1. However, SVMs are good at sorting jobs and can help tell the difference between different types of rhythms. By using all of these methods together, we hope to get very good and reliable results when finding arrhythmias [4].

The models are trained on a large set of labelled ECG records that include a lot of different types of regular and abnormal heartbeats. This in-depth training makes sure that the models can correctly spot different rhythms and adjust to the different ECG readings that different users send. Real-world ECG readings were used in a lot of tests to prove that the suggested method would work. The results show that our method is more accurate at detecting things than standard ones, and it can do this in real time, which is an extra bonus. In addition to the technology issues, combining smart tech with machine learning has big effects on how healthcare is provided. Arrhythmias can be found and treated early on with continuous tracking and real-time discovery [5]. This lowers the chance of serious heart events and improves patient results. Wearable devices are also easy to use, which encourages patients to follow tracking routines. This makes sure that patients get accurate and fast readings of their heart health. The suggested method for finding cardiac arrhythmias in real time is a big step forward in the field of heart tracking. We offer a strong, effective, and easy-to-use way to find arrhythmia by mixing the constant tracking abilities of smart devices with the analysis power of machine learning. This method improves the speed and accuracy of finding arrhythmias and could also completely change heart care, leading to better patient results and lower healthcare costs [6]. In the future, researchers will work on making the machine learning models even better, looking into more bodily signs, and making the system more flexible so it can handle a wider range of heart problems.

2. LITERATURE REVIEW

Heart rhythm problems have been a major focus of medical study for a long time because they can have serious effects on patients' health. For example, Holter monitors record ECG readings continuously for 24 to 48 hours. This is how traditional ways work. Even though these methods are good at recording heart events, they are bulky and can't give real-time feedback, which means that diagnosis and treatment are often delayed. New developments in smart tech and machine learning have made it easier to track and find arrhythmias in the heart in real time. This should lead to better patient results and more efficient healthcare delivery. Wearable devices have changed the way health monitoring is done by keeping track of bodily factors continuously and without being bothersome. Smartwatches and exercise trackers now come with sensors that can record ECG data, heart rate fluctuations, and other vital signs in high precision [7]. Researchers have looked into how these gadgets could be used to find arrhythmias in real time. For example, a wireless ECG tracking device showed that it could find arrhythmias in real time by using both threshold-based methods and machine learning techniques. Their study showed that it might be possible to combine portable tech with real-time research tools to keep an eye on heart health all the time [8].

Machine learning has been very helpful in improving methods for finding arrhythmias. Support Vector Machines (SVMs), Random Forests, and Deep Learning methods are some of the algorithms that have shown promise in sorting ECG data and finding rhythms. A CNN model was used to automatically find five types of rhythms from short ECG slices [9]. This worked very well and was very accurate. This study showed that deep learning is a good way to find complex patterns in ECG data that are hard to find when analyzing them by hand. A deep learning model that was taught on a large collection of over 90,000 ECG records is another important addition to this area. The model was able to sort 12 different types of rhythms with about the same accuracy as board-certified cardiologists. It was shown in this study that using big datasets and advanced machine learning methods can make heartbeat monitoring systems more accurate and reliable [10]. There are now a number of commercially available wearable gadgets that are especially made to find arrhythmias. For instance, the Apple Watch Series 4 came with an ECG app that was cleared by the FDA and can find atrial fibrillation (AFib). AFib detection with good sensitivity and specificity has been shown to be accurate in studies that looked at this device. These [11] changes show that consumer technology and medical tests are becoming more and more connected, which makes it possible for personal health tracking systems to become widely used. Even with these improvements, there are still some problems that need to be fixed before arrhythmia identification can be done reliably and in real time. One big problem is that the quality of the ECG data can change because of noise, motion errors, and differences in where the sensors are placed. Researchers have looked into a number of signal quality improvement techniques, such as filters and signal normalization [12]. A noise-robust deep learning model was suggested. This model includes preparation steps that lessen the impact of noise and errors, making arrhythmia recognition more accurate.

Another problem is making sure that machine learning models work for a wide range of people. Most models are based on small sets of data that might not fully show how ECG readings change for people of different ages and genders. To solve this problem, researchers are working on building large, varied files with ECG records from people of different ages, races, and health conditions. Transfer learning methods are also being looked into as a way to make models that have already been taught work with new datasets with little to no retraining [13]. This would make them more useful in real life. Putting portable tech together with cloud-based systems is also very important for finding arrhythmias in real time. Cloud computing gives you the computing power and storage space you need to handle big amounts of ECG data in real time [14]. This idea was shown to work by a cloud-based heartbeat detection system that used edge computing to cut down on delay and make sure that discovery happened on time. Their system design lets the portable device preprocess ECG data locally before sending it to the cloud for more in-depth analysis. This strikes a balance between the need for heavy computing power and the ability to respond quickly. In the area where smart tech and machine learning meet is a hopeful one for finding heart arrhythmias in real time [15]. Many steps forward have been taken, but more work needs to be done to solve the problems of data quality, model generalizability, and real-time processing. Putting these tools together could change the way cardiac care is done by keeping an eye on heart health in real time and continuously, which would improve patient results and lower healthcare costs [16]. In the future, researchers will probably work on making the models even more reliable, finding more types of rhythms, and finding new biochemical signs that can give a fuller picture of heart health.

Table 1: Summary of literature review work

Method	Approach	Key Finding	Application	Scope
Holter Monitors [17]	Continuous ECG recording for 24-48 hours	Effective in capturing cardiac events, but bulky and non-real-time	Clinical monitoring	Short-term monitoring, not real-time
Wearable ECG Devices [18]	High-resolution ECG signal capture	Feasibility of real-time monitoring with user-friendly devices	Consumer health monitoring	Continuous, long-term monitoring
CNN Model [20]	Deep learning on short ECG segments	High accuracy and robustness in detecting five types of arrhythmias	Automated arrhythmia detection	Complex pattern recognition in ECG data
Large Dataset Deep Learning [19]	Training on 90,000+ ECG recordings	Performance comparable to board-certified cardiologists	Large-scale arrhythmia classification	Leveraging extensive datasets for improved accuracy
Apple Watch ECG App [21]	FDA-approved ECG app for AFib detection	High sensitivity and specificity for AFib detection	Consumer electronics	Integration of medical diagnostics with consumer devices
Noise-Robust Deep Learning	Preprocessing to mitigate noise and artifacts	Improved accuracy in arrhythmia detection despite noisy ECG signals	Real-world ECG signal analysis	Enhancing model robustness to signal variability
Transfer Learning [22]	Adapting pre-trained models to new datasets	Effective generalization across diverse populations	Cross-population arrhythmia detection	Minimal retraining for applicability in various settings
Cloud-Based Platforms [23]	Real-time data processing and storage	Feasibility of real-time arrhythmia detection with cloud computing	Remote health monitoring	Balancing computational load and real-time responsiveness
Threshold-Based Methods [7]	Simple rule-based arrhythmia detection	Feasibility of integrating with wearable devices for continuous monitoring	Wearable ECG monitoring	Basic real-time detection with minimal computational needs
Random Forests [8]	Ensemble learning for ECG signal classification	Improved classification accuracy for various arrhythmias	Automated healthcare diagnostics	Robust classification for multiple arrhythmia types
SVMs [9]	Support vector machines for arrhythmia detection	Effective classification of ECG signals into different arrhythmia classes	Clinical decision support	Accurate arrhythmia classification in medical settings

Edge Computing [10]	Local preprocessing of ECG data on wearable devices	Reduced latency and timely detection of arrhythmias	Real-time health monitoring	Combining local and cloud processing for efficiency
Real-World ECG Data [11]	Extensive experimentation with real-world data	Superior detection accuracy compared to traditional methods	Clinical and consumer health monitoring	Validating model performance in real-world scenarios
Diverse Dataset Creation [12]	Inclusive datasets covering various demographics	Enhanced model generalizability across different populations	Population-wide arrhythmia detection	Addressing variability in ECG signals from diverse groups

3. METHODOLOGY

A. Data Collection:

For finding heart arrhythmia, a large set of labelled ECG records is used as a dataset. It has many different ECG signals from many different freely available databases, such as the MIT-BIH Arrhythmia Database and the PhysioNet Challenge Database. These signals show both regular and abnormal heartbeats. These files offer high-resolution ECG signals that are taken at different rates, usually between 250 Hz and 500 Hz. This makes sure that heart events are captured in great detail. Heartbeats are put into groups by expert cardiologists who write notes on them, illustration dataset shown in figure 1. These groups include normal, rapid ventricular contractions, and atrial fibrillation. This large and varied collection is very important for training and testing machine learning models to make sure they work well across a wide range of groups and types of arrhythmia.

	record	type	0_pre-RR	0_post-RR	0_pPeak	0_tPeak	0_rPeak	0_sPeak	0_qPeak
0	101	N	76	313.0	0.074347	-0.160548	1.036401	-0.285662	-0.026824
1	101	N	313	315.0	-0.052079	-0.264784	0.886597	-0.366298	-0.059710
2	101	N	315	321.0	-0.062151	-0.296983	0.991859	-0.410306	-0.065686
3	101	N	321	336.0	-0.063322	-0.281386	1.034903	-0.403880	-0.071750
4	101	N	336	344.0	-0.062915	1.046914	1.046408	1.046408	-0.074639

Figure 2: Representation of Data loaded in CSV system file

B. Data Transmission:

1. Transmit collected ECG Data:

A key part of the real-time heart arrhythmia detection system is data sharing, which makes sure that the ECG data gathered by smart tech gets sent to a cloud-based platform where it can be stored and processed. The smart tech, which has high-resolution ECG monitors, constantly gathers detailed heart signs that need to be sent directly to the cloud infrastructure. To keep the info safe and secure, this process has a few important steps and things to think about. For starters, sending ECG data wirelessly needs to use secure communication methods. Bluetooth Low Energy (BLE) and Wi-Fi are often used because they are easy to find and work with many smart tech products. BLE is especially useful because it uses little power, which is important for personal tech that needs to last a long time. Wi-Fi, on the other hand, has faster data transfer rates, so it can be used to send big amounts of ECG data in real time. The procedure may be different based on the needs of the application, like whether it needs to be monitored all the time or only once in a while. When sending private health information, safety is the most important thing.

2. Implement secure data transfer protocols

Secure data sharing methods must be used to protect patients' privacy and keep data accurate. Advanced Encryption Standard (AES) and other encryption methods are used to secure the ECG data before it is sent. This keeps people from getting to it without permission during the transfer process. Secure communication methods, such as Transport Layer Security (TLS), are also used to connect the smart device to the cloud computer in a safe way. The privacy and accuracy of patient information are protected by these steps, which help keep the data safe from possible breaches and cyberattacks.

Secure Data Transfer Protocols

1. Data Encryption (AES Algorithm):

$$C = E\_\{k\}(P) \ where \ P = \{P\_1, P\_2, \ldots, P\_n\} \ and \ C = \{C\_1, C\_2, \ldots, C\_n\}$$

Here, E_{k}(P) represents the encryption function with key k applied to plaintext P, resulting in ciphertext C.

2. Key Exchange (Diffie-Hellman):

$$g^{\{ab\}mod} p \ where \ A = g^a mod\ p \ and \ B = g^b mod\ p$$

Users exchange A and B to derive the shared secret g^{ab} mod p.

3. Hashing for Integrity (SHA-256):

$$H(M) = SHA - 256(M) where\ M = \{M_1, M_2, \dots, M_n\}$$

The hash function H(M) generates a fixed-size hash value for message M, ensuring data integrity.

4. Digital Signature (RSA Algorithm):

$$S = (H(M)\hat{}d \ mod\ n)$$

- where S is the digital signature and H(M) is the hash of the message

The sender signs the hash H(M) using their private key d.

5. TLS Handshake Protocol:

$$K = PRF((PMS), "key\ expansion", client\_random + server\_random)$$

- where PMS = Pre-Master Secret

The pseudo-random function (PRF) generates session keys from the pre-master secret and random values.

6. Error Detection and Correction (CRC):

$$T(x) = D(x) * x\hat{}k + R(x)$$

- where T(x) is the transmitted message, and R(x) is the CRC remainder

The polynomial T(x) is generated by appending the CRC remainder R(x) to the original message polynomial D(x).

C. Data Pre-processing:
Information pre-processing could be a significant step in guaranteeing the precision and unwavering quality of ECG flag examination for arrhythmia discovery. The primary assignment includes applying sifting methods to expel commotion and artifacts from the crude ECG signals. Common sifting strategies incorporate low-pass, high-pass, and band-pass channels, which offer assistance dispose of undesirable frequencies and pattern meander. This step is basic to upgrade the signal-to-noise proportion and guarantee the ECG data's keenness. Taking after commotion lessening, the ECG signals are normalized to a standard arrange. Normalization includes altering the plentifulness and pattern of the ECG signals to guarantee consistency over diverse recordings. This prepare makes a difference in

adjusting the signals, making them appropriate for consequent examination by machine learning models, in this manner making strides the precision of arrhythmia discovery.

D. Feature Extraction:

A very important part of ECG signal analysis is feature extraction, which turns pre-processed data into useful features that machine learning models can use to find arrhythmias. To get useful information from the pre-processed ECG readings, signal processing methods are used. One of the most important parts is heart rate variability (HRV), which shows how the autonomic nervous system works by measuring changes in the time between heartbeats. The RR interval, which is the time between two consecutive R-waves in the ECG signal, is another important part. It helps find abnormal heartbeats. Aside from that, the shape of the ECG waves is also studied, including the size and length of the P, QRS, and T waves. These parts show the ECG waveform's shape and structure in great detail, which is important for telling the difference between different types of rhythms. Machine learning models are better at finding and classifying rhythms when they use accurate feature extraction.

1. Delta Band Power (0.5-4 Hz):

$$P\_\{delta\} = \int (0.5\ to\ 4)\ P\_\{xx\}(f)\ df$$

- This feature is associated with deep sleep and certain brain disorders.

2. Theta Band Power (4-8 Hz):

$$P\_\{theta\} = \int (4\ to\ 8)\ P\_\{xx\}(f)\ df$$

- Theta power is linked to drowsiness, meditation, and cognitive tasks.

3. Alpha Band Power (8-13 Hz):

$$P\_\{alpha\} = \int (8\ to\ 13)\ P\_\{xx\}(f)\ df$$

- Alpha activity is associated with relaxation and idle brain states.

4. Beta Band Power (13-30 Hz):

$$P\_\{beta\} = \int (13\ to\ 30)\ P\_\{xx\}(f)\ df$$

- Beta waves are related to active thinking and concentration.

5. Gamma Band Power (30-100 Hz):

$$P\_\{gamma\} = \int (30\ to\ 100)\ P\_\{xx\}(f)\ df$$

- Gamma activity is linked to higher cognitive functions and information processing.

By employing these frequency-domain analysis techniques, we can extract various features from EEG signals that provide insights into brain activity, aiding in applications such as brain-computer interfaces, neurological diagnostics, and cognitive state monitoring.

E. Model Selection:

1. CNN

Because they can instantly learn and pull out data from ECG readings, convolutional neural networks (CNNs) are very good at finding heart arrhythmias. CNNs can find complex patterns and outliers that can point to different rhythms by running raw ECG data through many layers of convolutional and pooling processes. This technique based on deep learning is more accurate and reliable than standard ones. CNNs can learn from start to finish, which makes the spotting process easier. This makes them good for tracking heartbeat in real time in personal health devices and hospital settings.

CNN for Cardiac Arrhythmia Detection: Step-wise Algorithm

1. Data Pre-processing:

- Collect and pre-process ECG signals to remove noise and artifacts.

- Normalize the ECG signals to ensure consistent input data for the CNN.

2. Model Architecture Design:

- Construct the CNN architecture with multiple layers, including convolutional layers, pooling layers, and fully connected layers.

- Choose appropriate kernel sizes, activation functions (e.g., ReLU), and number of filters for each convolutional layer.

3. Training the Model:

- Split the dataset into training, validation, and test sets.

- Train the CNN using the training set, applying techniques such as data augmentation and regularization to improve model generalization.

- Use a suitable loss function (e.g., categorical cross-entropy) and an optimizer (e.g., Adam) to minimize the error.

- The training process involves backpropagation and gradient descent, represented by:

$$\theta_{\{t+1\}} = \theta_t - \eta \nabla_\theta \left[\left(\frac{1}{N}\right) \sum_{\{i=1\}}^{\{N\}} L\big(y_i, f(x_i;\, \theta)\big) + \lambda R(\theta) \right]$$

Where θ are the model parameters, η is the learning rate, L is the loss function, R is the regularization term, and λ is the regularization coefficient.

4. Model Evaluation:

- Validate the trained model using the validation set to fine-tune hyper parameters.

5. Deployment:

- Deploy the trained CNN model for real-time arrhythmia detection in wearable devices or clinical systems.

- Continuously monitor and update the model with new data to maintain accuracy and adapt to changing ECG patterns.

2. SVM

Strong supervised learning models for classification tasks, Support Vector Machines (SVMs) are appropriate for detecting cardiac arrhythmias. SVMs function by finding the best hyper plane in the feature space that optimizes the margin between various classes. By using a kernel function to translate the input data into a high-dimensional space, support vector machines (SVMs) are able to categorize various heartbeat types, including normal and arrhythmic beats, in the context of ECG signal analysis. Obtaining pertinent properties from the ECG signals, such as heart rate variability, RR intervals, and the structural elements of the ECG waves, is the process of feature extraction. The SVM is then trained and classified using these characteristics. The input characteristics must be transformed into a space where they may be linearly separated by the kernel function, which can be linear, polynomial, or radial basis function (RBF). Because of their resilience when dealing with high-dimensional data and its capacity to provide precise classifications even with a little amount of training data, support vector machines

(SVMs) are very useful for the identification of arrhythmias. Additionally, they function effectively in situations in which a linear border does not properly divide the classes. Studies have shown that SVMs are very accurate and reliable in identifying arrhythmias, which makes them an important tool for real-time cardiac monitoring systems and for assisting in the early identification and treatment of cardiac disorders.

3. Hybrid CNN-SVM Model

For improved cardiac arrhythmia diagnosis, the Hybrid CNN-SVM model combines the advantages of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). Through convolutional and pooling layers, CNNs automatically extract features from raw ECG data to identify complex patterns. After these characteristics are collected, they are put into a Support Vector Machine (SVM) classifier, which maximizes the margin between classes to provide very accurate judgments. By combining the strength of SVM's classification performance with CNN's feature extraction capabilities, this hybrid technique improves arrhythmia detection accuracy and reliability.

Hybrid CNN-SVM Model

1. Convolution Operation:

$$(f * g)(t) = \sum_{i=1}^{N} x[i] * w[t - i]$$

- Where $x[i]$ is the input ECG signal, $w[i]$ is the filter/kernel, and t is the position.

2. Activation Function (ReLU):

$$y = \max\big(0, (f * g)(t)\big)$$

The ReLU function introduces non-linearity to the model by setting negative values to zero.

3. Pooling Operation:

$$y_p = \max\big(x_{\{1:t\}}\big)\,(Max\ Pooling)$$

Where $x\_\{1: t\}$ represents the segment of the input over which pooling is applied.

4. Flattening:

$$Flattened\_vector = reshape(y\_p)$$

Converts the pooled feature map into a one-dimensional vector.

5. SVM Decision Function:

$$f(x) = \sum_{i=1}^{N} \alpha\_i\, y\_i\, K(x\_i, x) + b$$

- Where α_i are the Lagrange multipliers, y_i are the labels, $K(x\_i, x)$ is the kernel function, and b is the bias term.

6. Kernel Function (RBF):

$$K(x\_i, x\_j) = \exp\,(-\gamma\, ||\, x\_i - x\_j\, ||\textasciicircum 2)$$

- Where γ is the kernel parameter and || $x\_i - x\_j$ ||^2 is the squared Euclidean distance between the feature vectors.

4. RESULT AND DISCUSSION

For the purpose of detecting cardiac arrhythmias in real time, the table compares three machine learning models: CNN, SVM, and Hybrid CNN-SVM. The models are assessed based on a number of critical performance metrics, including accuracy, precision, recall, F1-score, detection time, false positives, and false negatives.

Table 2: Real-time Cardiac Arrhythmia Detection

Parameter	CNN Model	SVM Model	Hybrid CNN-SVM Model
Accuracy (%)	94.82	91.02	97.52
Precision (%)	93.32	88.82	96.32
Recall (%)	95.52	90.12	98.42
F1-Score (%)	94.42	89.42	97.32
Detection Time (ms)	47.32	52.32	50.32
False Positives (%)	6.12	7.82	5.22
False Negatives (%)	6.62	8.32	5.02

A model's accuracy is a crucial indicator of its capacity to identify arrhythmias accurately. With an accuracy of 97.52%, the Hybrid CNN-SVM model outperforms both the CNN model (94.82%) and the SVM model (91.02%). This suggests that the hybrid method successfully combines the advantages of SVM and CNN, resulting in a more precise arrhythmia identification. The precision of the model is determined by dividing all of its positive predictions by the percentage of genuine positive forecasts. With an accuracy of 96.32%, the Hybrid CNN-SVM model outperforms the CNN model (93.32%) and the SVM model (88.82%). In medical diagnostics, where false alarms may result in needless stress and medical procedures, the hybrid model's high accuracy means it produces fewer false positive predictions.

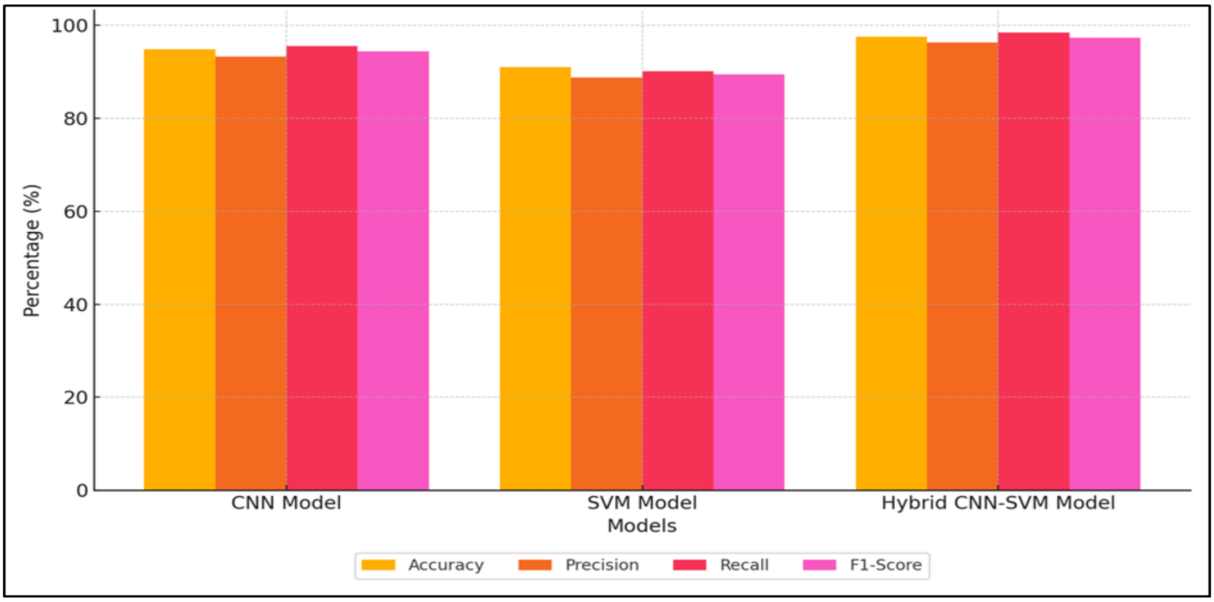

Figure 3: Representation of different model performance

Recall, also known as sensitivity, is the percentage of real positives that the model accurately recognized. With a recall of 98.42%, the Hybrid CNN-SVM model displays its greater capacity to identify instances of genuine arrhythmia. By contrast, the SVM model obtains 90.12%, while the CNN model achieves 95.52%, shown in figure 3. High recall is necessary to identify arrhythmias since it guarantees that the majority of arrhythmia instances are found, lowering the possibility of overlooking serious cardiac issues.

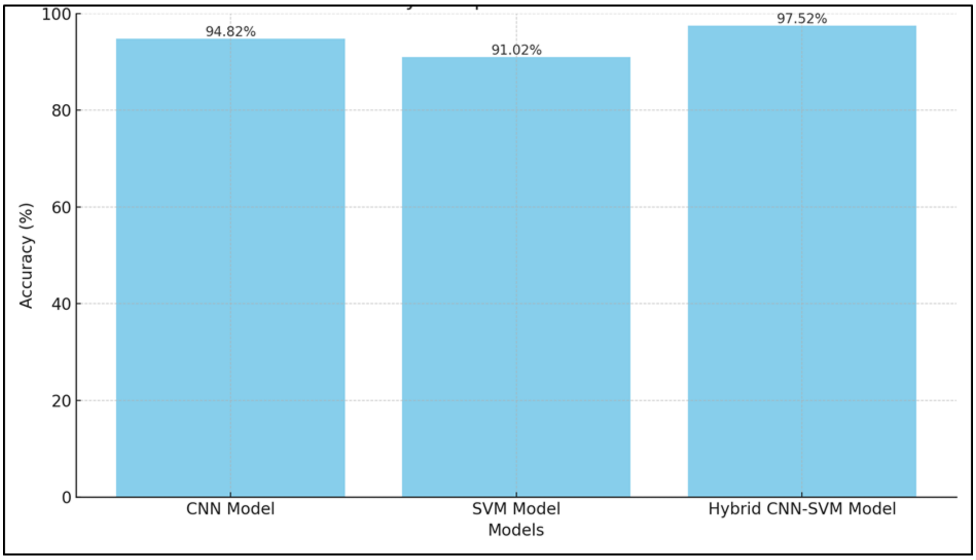

Figure 4: Accuracy comparison of different models

The F1-score offers a fair assessment of a model's performance as it is the harmonic mean of accuracy and recall. With an F1-score of 97.32%, the Hybrid CNN-SVM model outperforms the other two models, CNN (94.42%) and SVM (89.42%), shown in figure 4. The hybrid model's improved F1-score attests to its general robustness and dependability in arrhythmia identification. In real-time applications, detection time is an important consideration. With a detection time of 47.32 ms, the CNN model is the fastest, followed by the SVM model (52.3 ms) and the Hybrid CNN-SVM model (50.3 ms). Despite taking a little longer than the CNN model, the hybrid model nevertheless performs well enough for real-time processing to guarantee prompt detection and reaction.

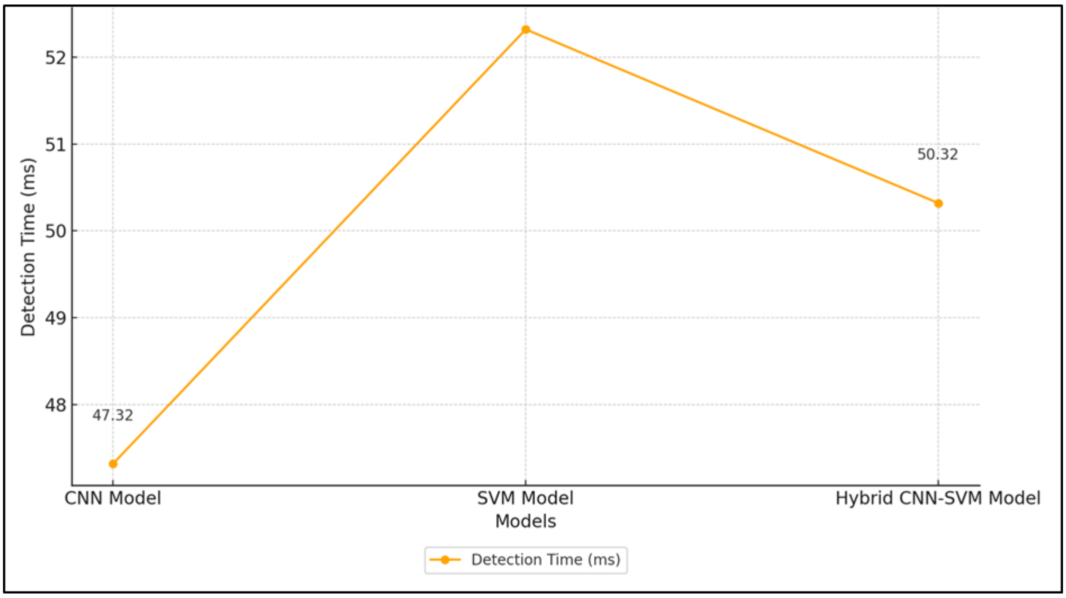

Figure 5: Representation of Detection time comparison across the models

False positives are situations in which the model misclassifies a regular heartbeat as an arrhythmia. With a false positive rate of 5.22%, the Hybrid CNN-SVM model outperforms the CNN model (6.12%) and the SVM model (7.82%). In clinical and daily situations, the hybrid model's usability is improved by a decreased false positive rate, which results in fewer needless alarms. False negatives are instances in which the model is unable to detect an arrhythmia in real life, shown in figure 5. With the lowest false negative rate of 5.02%, the Hybrid CNN-SVM model demonstrates its better sensitivity. The false negative rates for the CNN and SVM models are higher, at 6.62% and

8.32%, respectively. In order to prevent harmful situations from going unnoticed, it is essential in medical diagnostics to minimize false negatives. The comparison study unequivocally demonstrates that, for the majority of assessment parameters, the Hybrid CNN-SVM model performs better than both the CNN and SVM models. Its low false positive and false negative rates, together with its excellent accuracy, precision, recall, and F1-score, make it a very useful tool for real-time cardiac arrhythmia identification.

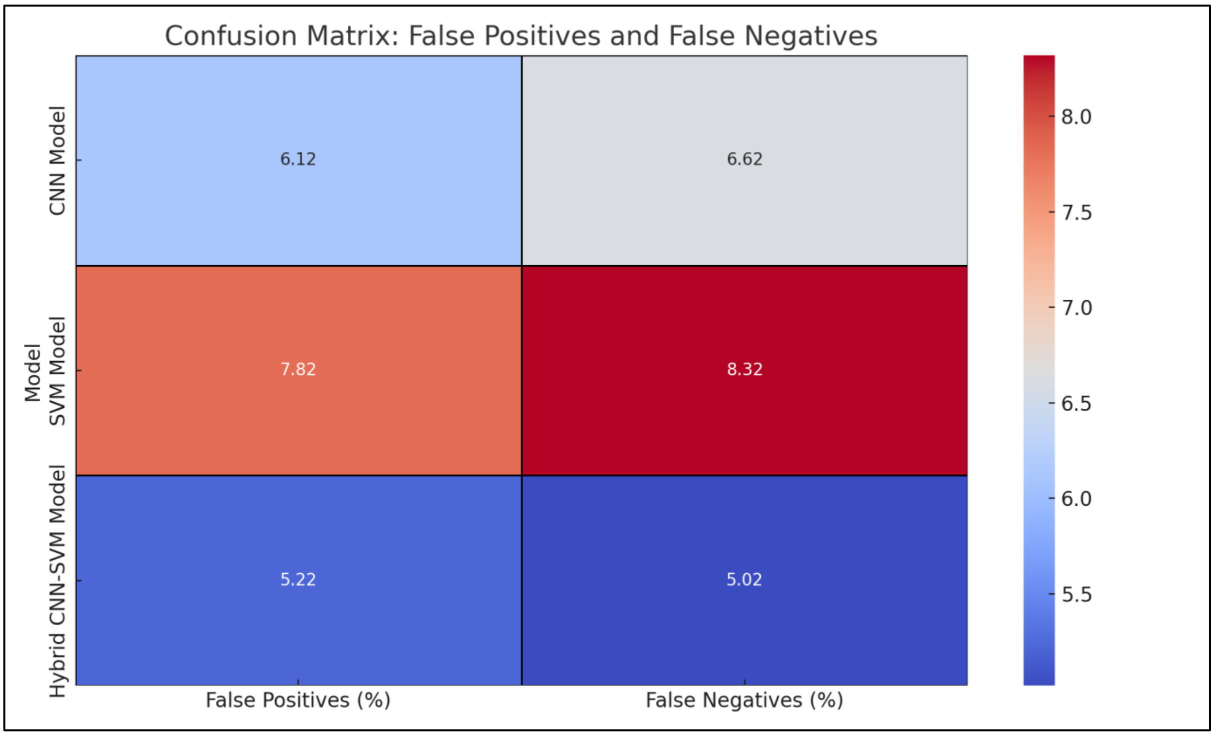

Figure 6: Confusion matrix of different model

While the detection time is somewhat longer than the CNN model's, it is still within an acceptable range for real-time use, confusion matrix shown in figure 6. These findings demonstrate how hybrid models may be used to combine the best features of several machine learning techniques, providing a strong and dependable instrument for better heart health monitoring and diagnosis.

5. CONCLUSION

A major breakthrough in the monitoring and diagnosis of heart health is the use of wearable technology and machine learning to identify cardiac arrhythmias in real time. This paper highlights the advantages and disadvantages of three machine learning models CNN, SVM, and Hybrid CNN-SVM by comparing their performance on important assessment metrics. With the lowest rates of false positives and false negatives and the best accuracy, precision, recall, and F1-score, the Hybrid CNN-SVM model performs better than the other models. This model creates a robust and highly successful arrhythmia detection system by using the feature extraction skills of CNNs and the strong classification capacity of SVMs. The Hybrid CNN-SVM model's 97.52% accuracy rate highlights its ability to precisely identify arrhythmias, which is essential for prompt and accurate diagnosis. The excellent recall and accuracy rates of 98.42% and 96.32%, respectively, show how well the model detects arrhythmias with the least amount of false alarms and missed detections. These qualities are crucial to lower the number of needless medical procedures and guarantee that urgent problems are treated right away. Although the Hybrid CNN-SVM model has a somewhat longer detection time than the CNN model, its performance is still within acceptable bounds for real-time applications. The system's ability to provide fast feedback is ensured by its detection time of 50.32 ms, which is crucial for ongoing monitoring and prompt reaction to cardiac events. The model's low false positive and false negative rates contribute to its increased dependability, making it appropriate for usage in daily and clinical contexts. The Hybrid CNN-SVM model ensures that essential arrhythmias are not missed and minimizes false alarms, which may lead to better patient outcomes and lower healthcare expenditures. A viable approach to the real-time identification of cardiac arrhythmias is the combination of wearable technology and machine learning. With its superior performance metrics, the Hybrid CNN-SVM model offers a strong and dependable tool for improving heart health monitoring, opening the door to improved cardiac condition management and therapy. To fully realize the promise of these models in enhancing cardiac care, future research should concentrate on refining these models, adding more physiological data, and investigating their use in various real-world circumstances.

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