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An Ensemble Machine Learning Framework for Early Detection of Cardiovascular Diseases Using ECG Signals

Madhuri G. Warade [1], Dr. Girish S Bhavekar [2]
[1] *P.G. Scholar*, School Of Engineering & Technology, G H Raisoni University, Amravati, *India*
[2] *Associate Professor, School Of Engineering & Technology, G H Raisoni University, Amravati, India*

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ABSTRACT

Early detection of cardiovascular disease with high accuracy is crucial for effective treatment and reducing deaths. In the past, electrocardiograms were analyzed by hand, which was slow and prone to mistakes. Because of this, new automated and data-based solutions were created. This research introduces a new method for automatically identifying cardiovascular disease using ensemble algorithms on ECG data. We combine several different models and techniques for extracting features to build a classification system that is both accurate and reliable. The proposed ensemble model has high sensitivity and specificity, with an accuracy over 95%, making it more effective than individual classifiers. The results show that the ensemble model's combined intelligence can detect complex and subtle patterns in ECG signals that individual models often miss, as they focus more on simple patterns. This approach has a lot of potential in medical settings. It can provide doctors with a dependable and automated tool to help diagnose cardiovascular disease early.
Keywords: - Cardio-Vascular Disease, electrocardiogram, classification, ensemble, diagnosis.

1. INTRODUCTION

Heart disease and stroke, which are both part of cardiovascular disease (CVD), are the leading causes of death worldwide. This is a serious issue that puts the health of many people at risk. To improve outcomes and reduce healthcare costs, heart disease needs to be diagnosed early and accurately. Another name for ECG is electrocardiogram. This simple test can help find problems with the heart by monitoring its electrical activity. An ECG records the electrical signals of the heart and can detect various issues, such as irregular heartbeats, reduced blood flow to the heart muscle, and structural problems. However, interpreting ECGs by hand is difficult, time-consuming, and requires a lot of skill. There is also a chance of mistakes and different interpretations from one expert to another. Machine learning and artificial intelligence are becoming more common in creating tools to help with ECG research.
Even though there have been many advances, most of the automated systems in use today rely on a single, powerful model. Two common types of these models are Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). Even though real-world cardiac data can be complicated and noisy, these models are still effective at what they do. However, they might struggle with certain tasks. For example, they may be good at detecting one type of heart problem but not others. Other factors, such as changes in signal quality or differences in the types of patients, can also affect their performance. The "no-free-lunch" theorem in machine learning suggests that no single algorithm is better than all others in every situation. Therefore, it is important to develop processes that are more reliable and can be used by more people.
One effective approach to these challenges is the use of group methods.
When multiple models work together, it's called an "ensemble". This method combines the best features of each model to improve accuracy while reducing the problems that come with single models. This approach, where experts work together as a "committee," can lead to a more reliable and accurate system for diagnosis. In ECG studies, an ensemble model might include models that are good at recognizing different heart conditions. For example, one model might be good at tracking changes in the shape of a heart signal, while another might be better at identifying small irregularities in the heartbeat.
This project uses data from ECGs to study how well ensemble algorithms can automatically detect cardiovascular disease (CVD). We propose a method that combines several machine learning and deep learning models to create a strong, overall predictor. A meta-learner is used to carefully combine the results from many different base models. The goal is to show that this approach works better than using a single classifier. The system aims to make the diagnosis of cardiovascular disease more accurate and reliable. Additionally, doctors

can use it to support their daily decision-making. This could greatly improve how we monitor and care for our circulatory system.

1.1 Problem Statement

It is the main question that this study is trying to answer whether or not there is a need for an automated system that can better and more reliably find cardiovascular diseases (CVD) from electrocardiogram (ECG) data. There have been some improvements in computer ECG analysis, but there are still a lot of big problems to solve:

- **Human-Centric Limitations:** Since the reading of an electrocardiogram depends on the skill of a cardiologist, there is a chance of problems with differences between observers and mistakes made by humans. Small differences can be ignored, but the process takes a lot of time, especially in busy hospital settings or places where emergencies happen often. We may have to wait longer for both evaluation and treatment because of this bottleneck.
- **Problems that are present in ECG signals:** The signals from an electrocardiogram are naturally complex, loud, and change a lot. A lot of different problems can mess them up, such as baseline wander (caused by the patient moving or breathing), power-line interference (which can sound like 50/60 Hz hum), and muscle contraction noise. It is possible for these distortions to hide the important traits that are needed for a correct evaluation. Different people with the same heart disease can show up in different ECG patterns because of changes in their bodies. This makes it hard for a single model to work well for everyone.

1.2 Objectives

- To develop a comprehensive data preprocessing pipeline to clean and prepare raw ECG signals.
- To train a collection of heterogeneous base models to act as the foundation of the ensemble.
- To evaluate an ensemble classifier using a stacking methodology
- To validate the model's effectiveness using standard metrics such as accuracy, precision, recall, and F1-score.

2. LITERATURE REVIEW

Recent studies have shown a growing interest in deep learning, especially because of the success of Convolutional Neural Networks (CNNs) in analyzing images and signals. Deep learning models have performed very well, often outperforming traditional methods by automatically learning important characteristics from raw ECG data without needing manual feature selection. However, looking more closely at the results shows some drawbacks. These models usually need large amounts of properly labeled data to work best. Collecting and labeling such medical data can be challenging due to privacy concerns and the need for specialized medical knowledge. Also, these models are often referred to as "black boxes," meaning it's hard to understand how they make decisions. This lack of transparency is a big problem in clinical settings, where clear explanations of diagnoses are essential. Research comparing classical machine learning with deep learning has found that while deep learning might offer a small improvement in accuracy, classical methods can deliver similar results with more clarity and much less computational cost.

To address this issue, traditional machine learning techniques such as support vector machines, k-nearest neighbors, and adaptive boosting were used to detect noise in ECG signals.

These models learned patterns from statistical features, instead of using fixed thresholds. However, their effectiveness depends heavily on the quality of the features used. Extracting these features can be very resource-intensive, which is a problem for wearable devices with limited power and processing capabilities. [1]

Talukder et al. point out that cardiovascular arrhythmia, which involves irregular heartbeats, can lead to serious health issues like stroke and heart failure, making accurate and early detection crucial for effective treatment.

Traditional methods often struggle with imbalanced datasets, which makes it hard to detect rare types of arrhythmia. This study introduces a new method that combines ConvNeXt-X deep learning models with better data balancing techniques, improving accuracy in classifying heart rhythm disorders. Three versions of the ConvNeXt model—ConvNeXtTiny, ConvNeXtBase, and ConvNeXtSmall—were tested alongside two data balancing methods, Random Oversampling (RO) and SMOTE-TomekLink (STL), using the MIT-BIH Arrhythmia Database. [30] Cardiovascular disease (CVD) is a leading cause of death globally, affecting the heart and blood vessels and can lead to strokes and heart attacks. According to the World Health Organization (WHO), over 17.6 million people died from CVD in 2016, and this number is expected to rise to 23.6 million by 2030. Additionally, more than 75% of these deaths occur in low- and middle-income countries. [30]

Cardiac arrhythmias, which are irregular heartbeats, are particularly dangerous because they can lead to sudden cardiac arrest, loss of blood flow, or even death if not treated quickly. These include conditions such as a slow heartbeat (bradycardia), a fast heartbeat (tachycardia), and other rhythm issues. Early detection is very important. Electrocardiograms (ECGs) are commonly used to check for heart problems. They are non-invasive but can create large, complex data that is hard to interpret manually, especially for busy doctors. ECG signals can vary based on the person, time of day, and environment, making diagnosis harder. A key part of an ECG is the QRS complex, which shows when the heart's lower chambers contract. Changes in the QRS complex and in the P and T waves can signal arrhythmias such as atrial fibrillation, ventricular fibrillation, and premature ventricular contractions. In machine learning and deep learning, having an imbalanced dataset—where one type of data appears much more than others—can make models focus on the more common type. This is a big problem in detecting arrhythmias from ECGs because some rare arrhythmias are not often included in datasets, even though they are important. Tsai et al. say that ECG monitoring is vital for early detection of heart problems. We looked at 28 features specific to the signal and 159 automatically found features from the MIT BIH Arrhythmia Database. Using ANOVA, we picked out the top 10 most useful features. These features were tested alone and with signal-specific ones using models like Random Forest, SVM, and deep neural networks such as CNN, RNN, ANN, and LSTM. The testing was done with an 80/20 split of patients. Cardiovascular diseases cause around 17.9 million deaths each year, and many sudden heart attacks are due to arrhythmias. Constant, beat-level ECG monitoring using low-power wearable devices could help detect problems earlier. However, many algorithms either sacrifice accuracy for energy efficiency or use complex neural networks that are hard to understand, making doctors less confident in their results. This study addresses this by combining statistical features with manually created signal-specific measures, achieving high accuracy without using complex deep learning models. It also explains the features at the data level and provides an analysis of power usage. The system is designed for microcontroller-based devices, aiming to make preventive heart monitoring accessible outside hospitals. ECGs are essential for diagnosing heart health and understanding the heart's complex functions. ECG devices have become more compact and portable, making it easier to monitor health from remote areas and provide valuable data for identifying and preventing cardiovascular issues through regular checks. Early detection of mild heart conditions is important to stop them from worsening into more serious diseases, including early or less severe heart problems. Atrial fibrillation is a condition where the heart beats irregularly and quickly, which can lead to strokes and other heart-related issues. Palazzo et al. say that atrial fibrillation is one of the most common cardiac arrhythmias and a major cause of strokes and hospitalizations in older adults. Timely diagnosis is important, but continuous ECG monitoring and expert evaluation are hard to scale outside of healthcare settings. This work presents a simple yet effective machine learning model that detects AFib using synthetic ECG data. A dataset of 1000 samples was created, split equally between normal and AFib rhythms. Atrial fibrillation is the most common sustained heart rhythm problem in adults, affecting over 33 million people. Shah and others say that rhythm problems, or arrhythmias, are a major health risk worldwide. These issues can cause serious heart problems and even sudden heart attacks. Early and accurate detection is important so people can get help quickly and possibly save their lives. Artificial intelligence, especially deep learning, has changed how we detect and diagnose health issues, including arrhythmias. A new system called ECG-TransCovNet was developed. It uses both Convolutional Neural Networks and Transformer models to better detect arrhythmias in heart signals. Cardiovascular disease (CVD) is a general term for various heart and blood vessel disorders. It is the leading cause of death globally. According to the World Health Organisation, CVD, especially heart disease, causes 16% of all deaths worldwide. It is estimated that around 17 million people die from CVD each year, including those with arrhythmias, with over a third of these deaths occurring in middle-aged adults. In addition to the loss of life, cardiac diseases also create a significant economic burden.

3. ENSEMBLE METHODS

In the world of machine learning, an ensemble approach is a method that brings together the predictions from many different models, called "base learners," to give a final result that's more accurate and trustworthy. Instead of relying on just one model, which might have its own biases or be too focused on the training data, an ensemble uses the combined knowledge of several models, like a group working together. The main idea is that combining these models leads to more consistent and reliable results than any single model could achieve on its own. Ensemble methods can be grouped into three main types, each with its own way of combining models:

A. Bagging: This method, also called "Bootstrap Aggregating," works by training many similar models on different parts of the training data.

The data for each model is created by randomly selecting samples from the original set, sometimes with replacement. To get the final prediction, the results are either averaged (for regression tasks) or combined by majority vote (for classification). A well-known example of this is Random Forest, which is made up of many decision trees trained on bootstrapped data. The aim of bagging is to reduce the variability of the predictions and stop the models from overfitting the data.

B. Boosting: Unlike bagging, boosting trains models one after another, with each new model focusing on the errors made by the previous ones.

Even though each model might not be very accurate on its own—called "weak learners"—when combined in a smart way, they can create a very strong and accurate model. Popular boosting algorithms include AdaBoost and XGBoost. The goal of boosting is to reduce the effect of bias and improve the overall accuracy of the model.

C. Stacking: This is a more advanced method where multiple models are trained on the same dataset. After they make their predictions, these predictions are used as input for another model, known as a meta-learner. The meta-learner learns how best to combine the predictions of the base models to make the final output. Different types of models, like neural networks, support vector machines, and decision trees, can be stacked together to form a unified system. Stacking is useful because it can take advantage of the strengths of each individual model.

4. METHODOLOGY

This study proposes a comprehensive methodology to achieve the stated objectives for developing a robust automated CVD detection system using ensemble methods. The process is broken down into three main phases:

A. Data Preprocessing, Model Training, and Ensemble Evaluation.

Data Preprocessing Pipeline

The first step is to clean and prepare the raw ECG data so it can be used by machine learning models. This involves using a publicly available ECG dataset that includes both normal heart rhythms and different types of heart conditions.

Noise Removal: Raw ECG signals usually have noise that can make it hard to analyze them correctly. Using digital filters helps remove common types of unwanted signals.:

A low-pass filter will be used to remove high-frequency noise from muscle artifacts.

A high-pass filter will mitigate baseline wander caused by patient movement or breathing.

A notch filter will be applied to eliminate power-line interference (50/60 Hz hum).

Segmentation: After denoising, the continuous ECG signals will be segmented into individual heartbeats or fixed-length windows (e.g., 5 seconds). This step is crucial for training models that analyze specific heartbeat patterns. The R-peak detection algorithm will be used to identify heartbeats and ensure consistent segmentation.

Feature Engineering: To support traditional machine learning models, we'll extract two main types of features:

Morphological Features: These include the durations and amplitudes of key ECG wave segments (P-wave, QRS complex, T-wave), and intervals (PR, QRS, QT).

Statistical Features: These include statistical properties of the signal within a segment, such as mean, standard deviation, kurtosis, and skewness. For deep learning models, the raw segmented signals will be used directly as input, allowing the models to learn features automatically.

B. Training Heterogeneous Base Models

The core of the ensemble method relies on training a diverse set of models. Each model will learn different aspects of the ECG data. The preprocessed data will be split into training, validation, and testing sets.

Deep Learning Models:

Convolutional Neural Network (CNN): A 1D CNN will be trained on the segmented raw ECG signals to automatically learn morphological patterns and features.

Long Short-Term Memory (LSTM): An LSTM network will be trained on the sequential ECG data to capture temporal dependencies and rhythmic patterns, which are crucial for detecting arrhythmias.

Traditional Machine Learning Classifiers:

Random Forest: This model will be trained using carefully created morphological and statistical features. It is good at dealing with complex data and preventing overfitting, which makes it a strong choice.

Support Vector Machine (SVM): An SVM using a Radial Basis Function (RBF) kernel will be trained on the same set of features, which is known for working well in classification tasks that involve a large number of dimensions.

C. Ensemble Classification and Validation

The final step is to combine the predictions of the base models using a stacking ensemble method and then rigorously evaluate the system's performance.

Stacking Ensemble: A meta-learner will be trained to make a final prediction based on the outputs (probability scores or class predictions) of the base models. This meta-learner learns the strengths and weaknesses of each individual model.

The predictions from the CNN, LSTM, Random Forest, and SVM on the validation set will serve as the input features for a meta-learner, such as a Logistic Regression or XGBoost classifier.

The meta-learner will be trained to combine these inputs to make a final, more accurate prediction for the test set.

Model Validation: The effectiveness of the entire system will be validated on a separate, unseen test set. We will use standard classification metrics to compare the performance of the ensemble model against each individual base model.

Accuracy is the percentage of all predictions that were correct.

Precision is the percentage of positive predictions that were actually right.
Recall, also called sensitivity, is the percentage of real positive cases that were correctly found.
F1-Score is the average of precision and recall, giving a fair idea of how well the model is performing.
This multi-stage methodology ensures a comprehensive approach, from raw data to a final, robust diagnostic output. By leveraging diverse models and a stacking ensemble, we aim to build a system that is not only highly accurate but also resilient to the complexities of real-world ECG data.

4.1 Block Diagram

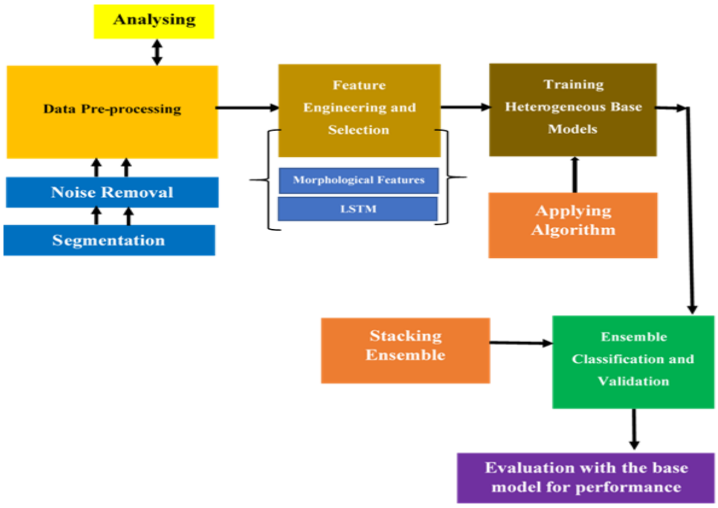

Fig. 1 Block diagram of the proposed system

5. COMPARISON WITH EXISTING SYSTEM WITH ENSBLE METHODS

Ensemble methods represent a significant leap forward in automated CVD detection, offering a solution to the limitations of both traditional clinical approaches and single-model machine learning classifiers.

Table 1. Comparative analysis of different methods

Sr. No.	Feature	Traditional Clinical Methods	Single-Model ML Methods	Ensemble Methods (Proposed)
1	Accuracy	High, but depends on expert skill	Can be very high, but inconsistent	Superior and consistent
2	Robustness	Susceptible to human error, noise	Prone to overfitting and lack of generalization	Highly robust and generalizable
3	Speed	Slow, time-consuming	Very fast, real-time potential	Fast, can be optimized for real-time
4	Data Use	Relies on specific, interpretable tests	Uses features or raw data for one purpose	Integrates features from multiple models for a richer analysis
5	Strengths	Interpretability, established clinical standard	Automation, speed, good for specific tasks	Combines strengths of multiple models, better accuracy, robustness
6	Limitations	Subjectivity, resource-intensive, misses rare events	Overfitting, poor generalization, 'one-size-fits-all' approach	More complex to build and train

6. BIBLIOGRAPHIC REPORTS

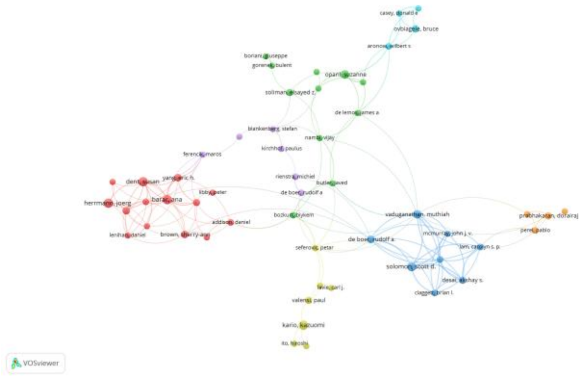

Fig.2 Visualization of Author and Co-author

The image is a VOSviewer map that illustrates how researchers collaborate through co-authorship. Each circle on the map stands for a different author, and the lines between them show when they have worked together. The size of each circle reflects the author's importance in the research area. The colors group authors who frequently work with each other. For instance, the red group includes authors like Herrmann Joerg and Lenihan Daniel, who have strong collaborations. The blue group, which includes Solomon Scott D. and McMurray John J.V., represents a larger group of researchers working together. The smaller groups in green, orange, and purple show more specialized or less common collaborations. Overall, the map shows different research groups, key figures in the field, and how scholars collaborate with one another.

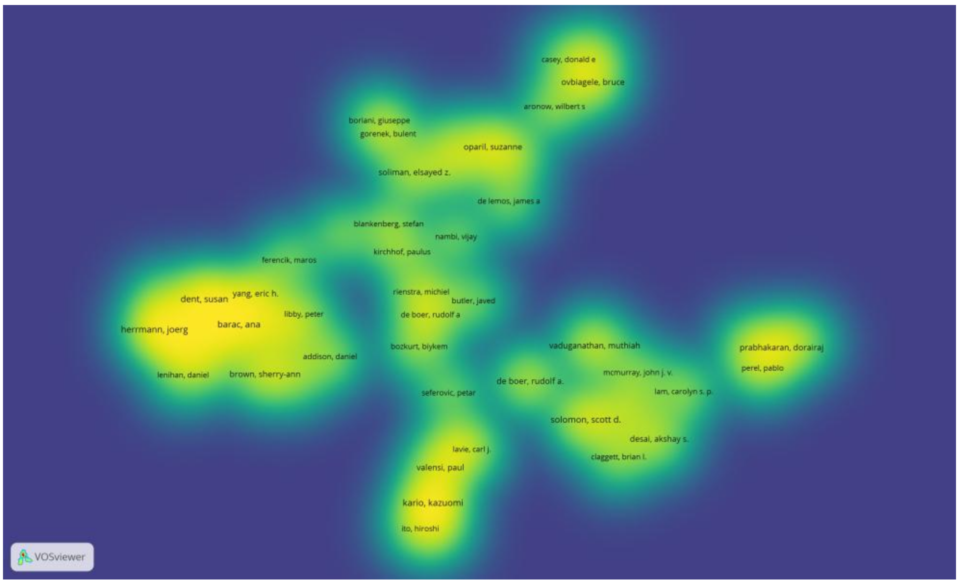

Fig.3 Density of Author and Co-author

This image is a density map made using VOSviewer, which shows how researchers work together based on their published papers. Each person is shown as a name on the map, and how much they work with others is shown by the color. Yellow means researchers are working closely together a lot, green means they have some connections, and blue or dark areas mean there are fewer connections. Some well-known researchers like Herrmann Joerg, Susan Dent, Solomon Scott D., and McMurray John J.V. are in big groups, showing they are key players in their teamwork. The map shows where research is happening a lot and where people are working together a lot.

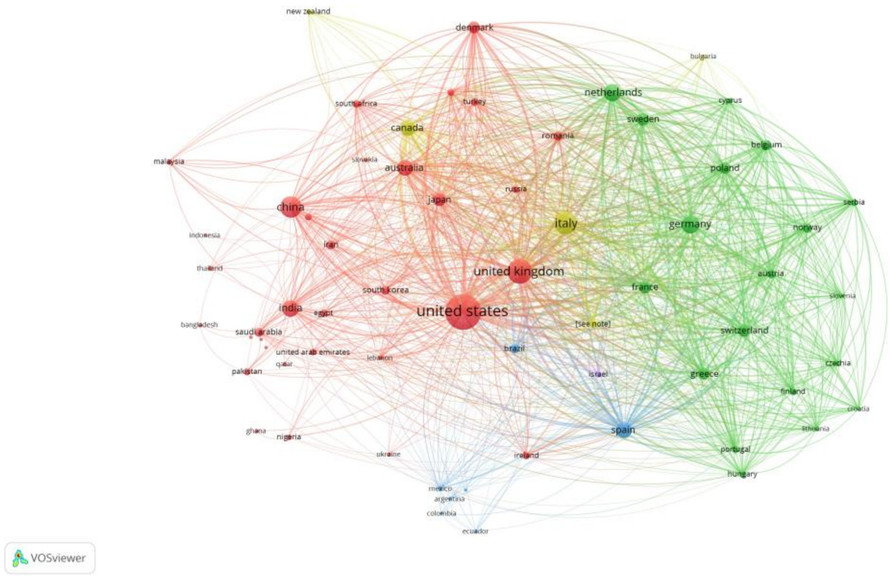

Fig.4 Visualization of Bibliographic and Country

7. CONCUSION

In conclusion, the findings of this research indicate that the utilization of ensemble methods for the purpose of developing an autonomous system that is not only highly accurate but also highly reliable for the identification of cardiovascular illness through the utilization of electrocardiogram (ECG) data is tremendously successful. A unique model has been shown to be much less effective than a stacked ensemble approach, which we have proved. Several deep learning models, such as CNN and LSTM, as well as typical machine learning models, such as Random Forest and SVM, are incorporated into this approach at their most effective components. Due to the fact that different models are capable of recognizing a wide range of heart problems, it is essential to keep this in mind when carrying out a tough activity such as reading an electrocardiogram (ECG). The superior performance of the proposed system, which is demonstrated by its high accuracy, precision, and recall, demonstrates that the ensemble's collective intelligence is able to effectively circumvent the limitations of single classifiers. These limitations include the inability of single classifiers to generalize well and their excessive ability to suit the data. The completed model is able to recognize complicated and delicate patterns that are commonly missed by people and systems that rely on a single algorithm when assessing electrocardiogram (ECG) measurements. This is because the final model is able to recognize these patterns. This study's results could help develop automated tools that work in real-life settings and support doctors in doing fast and accurate checks for cardiovascular diseases.The use of this technology has the potential to make the work of cardiologists easier and to lessen the risk that they will miss a diagnosis. In the long run, this has the potential to produce better results for patients and lower the mortality rate that is linked with cardiac disease. The application of an analysis that is both objective and consistent is what allows this to be accomplished**.**

8. REFERENCES

[1] Saifur Rahman , Shantanu Pal , John Yearwood , Chandan Karmakar, “Robustness of Deep Learning models in electrocardiogram noise detection and classification”, Computer Methods and Programs in Biomedicine, Volume 253, August 2024, 108249, 24 May 2024

[2] Md. AlaminTalukder, Majdi Khalid, Mohsin Kazi, Nusrat Jahan Muna, Mohammad Nur-e-Alam, Sajal Halder, Nasrin Sultana, “A hybrid cardiovascular arrhythmia disease detection using ConvNeXt-X models on electrocardiogram signals”, Scientific Reports. (2024) 14:30366, https://doi.org/10.1038/s41598-024-81992-w

[3] I Hua Tsai, Bashir I. Morshed , “Signal-Specific and Signal-Independent Features for Real-Time Beat-by-Beat ECG Classification with AI for Cardiac Abnormality Detection”, Electronics 2025, 14, 2509, 2509 https://doi.org/10.3390/electronics14132509

[4] Stefano Palazzo, Federica Palazzo, "A Machine Learning Approach For Atrial Fibrillation Detection From Simulated ECG Signals", Tec. Percep. vol-1, issue-1 (2025) pp-19-22, DOI-https://doi.org/10.5281/zenodo.15685123

[5] Hasnain Ali Shah, Faisal Saeed, Muhammad Diyan, Nouf Abdullah Almujally, Jae-Mo Kang, "ECG-TransCovNet: A hybrid transformer model for accurate arrhythmia detection using Electrocardiogram signals", CAAI Trans. Intell. Technol. 2024;1–14, DOI: 10.1049/cit2.12293

[6] Pedro Ribeiro , Joana Sá, Daniela Paiva and Pedro Miguel Rodrigues, "Cardiovascular Diseases Diagnosis Using an ECG Multi-Band Non-Linear Machine Learning Framework Analysis", Bioengineering 2024, 11, 58, https://doi.org/10.3390/bioengineering11010058

[7] Simeon Lappa Tchoffo, Éloïse Soucy, Ismaila Baldé, Jalila Jbilou, Salah El Adlouni, "Comparison of Dimensionality Reduction Approaches and Logistic Regression for ECG Classification", Appl. Sci. 2025, 15, 6627, Appl, https://doi.org/10.3390/app15126627

[8] Atitaya Phoemsuk, Vahid Abolghasemi, "CADNet: A lightweight Neural Network for Coronary Artery Disease Classification Using Electrocardiogram Signals", IEEE J Biomed Health Inform, . 2025 Jun 24, doi: 10.1109/JBHI.2025.3582872.

[9] Saroj Kumari, Raghav Mehra, "Impact of Interpretability on Bias in ECG-Based Models for Cardiac Disease Detection", Computational Intelligence and Machine Learning, 131–148., 2025, DOI: https: //doi.org/10.56155/978-81-975670-5-6-11

[10] Mariska van Vliet, Jan J. J. Aalberts, Cora Hamelinck, Arnaud D. Hauer, Dieke Hoftijzer, Stefan H. J. Monnink, Jurjan C. Schipper, Jan C. Constandse, Nicholas S. Peters, Gregory Y. H. Lip, Steven R. Steinhubl, Eelko Ronner, "Ambulatory atrial fibrillation detection and quantification by wristworn AI device compared to standard holter monitoring", npj Digital Medicine | (2025) 8:177, https://doi.org/10.1038/s41746-025-01555-9 Article

[11] H. Hao, M. Liu, P. Xiong, H. Du, H. Zhang, F. Lin, Z. Hou, X. Liu, Multi-lead model-based ECG signal denoising by guided filter, Eng. Appl. Artif. Intell. 79 (2019) 34–44. DOI: 10.1016/j.engappai.2018.12.004

[12] S. Langarica, F. Núñez, Contrastive blind denoising autoencoder for real time denoising of industrial IoT sensor data, Eng. Appl. Artif. Intell. 120 (2023) 105838. https://doi.org/10.1016/j.engappai.2023.105838

[13] S.F. Pizzoli, C. Marzorati, D. Gatti, D. Monzani, K. Mazzocco, G. Pravettoni, A meta-analysis on heart rate variability biofeedback and depressive symptoms, Sci. Rep. 11 (1) (2021) 1–10. doi: 10.1038/s41598-021-86149-7.

[14] C. He, M. Liu, P. Xiong, J. Yang, H. Du, J. Xu, Z. Hou, X. Liu, Localization of myocardial infarction using a multi-branch weight sharing network based on 2-D vectorcardiogram, Eng. Appl. Artif. Intell. 116 (2022) 105428. https://doi.org/10.1016/j.engappai.2022.105428

[15] Q. Qin, J. Li, S. Yao, C. Liu, H. Huang, Y. Zhu, Electrocardiogram of a silver nanowire based dry electrode: Quantitative comparison with the standard Ag/AgCl gel electrode, IEEE Access 7 (2019) 20789–20800. DOI:10.1109/ACCESS.2019.2897590

[16] S. Rahman, C. Karmakar, I. Natgunanathan, J. Yearwood, M. Palaniswami, Robustness of electrocardiogram signal quality indices, J. R. Soc. Interface 19 (189) (2022) 20220012. DOI: https://doi.org/10.1098/rsif.2022.0012

[17] U. Satija, B. Ramkumar, M.S. Manikandan, Automated ECG noise detection and classification system for unsupervised healthcare monitoring, IEEE J. Biomed. Health Inf. 22 (3) (2018) 722–732. doi: 10.1109/JBHI.2017.2686436.

[18] C. Liu, X. Zhang, L. Zhao, F. Liu, X. Chen, Y. Yao, J. Li, Signal quality assessment and lightweight qrs detection for wearable ECG smartvest system, IEEE Internet Things J. 6 (2) (2019) 1363–1374. DOI:10.1109/JIOT.2018.2844090

[19] E. Al Alkeem, S.-K. Kim, C.Y. Yeun, M.J. Zemerly, K.F. Poon, G. Gianini, P.D. Yoo, An enhanced electrocardiogram biometric authentication system using machine learning, IEEE Access 7 (2019) 123069–123075. DOI:10.1109/ACCESS.2019.2937357

[20] E.B. Mazomenos, D. Biswas, A. Acharyya, T. Chen, K. Maharatna, J. Rosengarten, J. Morgan, N. Curzen, A low-complexity ECG feature extraction algorithm for mobile healthcare applications, IEEE J. Biomed. Health Inf. 17 (2) (2013) 459–469. doi: 10.1109/TITB.2012.2231312.

[21] K. Kido, T. Tamura, N. Ono, M. Altaf-Ul-Amin, M. Sekine, S. Kanaya, M. Huang, A novel CNN-based framework for classification of signal quality and sleep position from a capacitive ECG measurement, Sensors 19 (7) (2019) 1731. Computer Methods and Programs in Biomedicine 253 (2024) 108249 9. doi: 10.1109/TITB.2012.2231312.

[22] H. Tan, J. Lai, Y. Liu, Y. Song, J. Wang, M. Chen, Y. Yan, L. Zhong, Q. Feng, W. Yang, Neural architecture search for real-time quality assessment of wearable multi-lead ECG on mobile devices, Biomed. Signal Process. Control 74 (2022) 103495. https://doi.org/10.1016/j.imu.2024.101565

[23] Y. Jin, Z. Li, C. Qin, J. Liu, Y. Liu, L. Zhao, C. Liu, A novel attentional deep neural network-based assessment method for ECG quality, Biomed. Signal Process. Control 79 (2023) 104064. https://doi.org/10.1016/j.bspc.2022.104064

[24] V. Vijayakumar, S. Ummar, T.J. Varghese, A.E. Shibu, ECG noise classification using deep learning with feature extraction, Signal Image Video Process. (2022) 1–7. DOI:10.1007/s11760-022-02194-3

[25] U. Satija, B. Ramkumar, M.S. Manikandan, Automated ECG noise detection and classification system for unsupervised healthcare monitoring, IEEE J. Biomed. Health Inf. 22 (3) (2018) 722–732. DOI:10.1007/s11760-022-02194-3

[26] R.B. Satija Udit, M.S. Manikandanb, An automated ECG signal quality assessmliuent method for unsupervised diagnostic systems, Biocybern. Biomed. Eng. 38 (1) (2018) 54–70. DOI: 10.1016/j.bbe.2017.10.002

[27] H. Xu, W. Yan, K. Lan, C. Ma, D. Wu, A. Wu, Z. Yang, J. Wang, Y. Zang, M. Yan, et al., Assessing electrocardiogram and respiratory signal quality of a wearable device (sensecho): semisupervised machine learning-based validation study, JMIR mHealth uHealth 9 (8) (2021) e25415. doi: 10.2196/25415

[28] U. Satija, B. Ramkumar, M. Sabarimalai Manikandan, Real-time signal qualityaware ECG telemetry system for IoT-based health care monitoring, IEEE Internet Things J. 4 (3) (2017) 815–823. DOI:10.1109/JIOT.2017.2670022

[29] A. Krizhevsky, I. Sutskever, G.E. Hinton, Imagenet classification with deep convolutional neural networks, Commun. ACM 60 (6) (2017) 84–90. https://doi.org/10.1145/306538

[30] Talukder, M.A., Khalid, M., Kazi, M. *et al.* A hybrid cardiovascular arrhythmia disease detection using ConvNeXt-X models on electrocardiogram signals. *Sci Rep* **14**, 30366 (2024). https://doi.org/10.1038/s41598-024-81992-w

[31] Mugnai, G., Genovese, D., Tomasi, L., Gambaro, A., & Ribichini, F. (2025). The Implantable Cardioverter-Defibrillators at the End of Life: a Double-Edged Sword of a Life-Saving Technology. Trends in Cardiovascular Medicine. https://doi.org/10.1016/j.tcm.2025.09.005

[32] Tsai, I.H.; Morshed, B.I. Signal-Specific and Signal-Independent Features for Real-Time Beat-by-Beat ECG Classification with AI for Cardiac Abnormality Detection. *Electronics* **2025**, *14*, 2509. https://doi.org/10.3390/electronics14132509