RESEARCH PAPER

Deep Learning Based Ecg Signal Analysis for Cardiac Disease Detection Using AI

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Abstract**—** Electrocardiogram (ECG) signal analysis is an essential task in the early diagnosis of cardiovascular diseases. Manual analysis of ECG signals is a time-consuming process and also vulnerable to human errors. This paper proposes an intelligent web-based ECG diagnosis system using a hybrid Convolutional Neural Network and Variational Autoencoder (CNN-VAE) model for automated cardiac disease classification. The proposed system preprocesses the raw ECG signals, extracts relevant features from the ECG signals using deep learning techniques, and classifies cardiac abnormalities with high accuracy. A full-fledged web application was developed using Flask to upload the dataset, train the model, predict the results, visualize the performance, and perform Explainable AI analysis. Experimental results on standard ECG datasets show that the proposed approach provides a reliable classification performance compared to the existing machine learning techniques. This system can be used to assist doctors in accurate and early diagnosis of cardiac diseases.

Keywords**—** *ECG Classification, Deep Learning, CNN-VAE, Flask Web Application, Medical AI, Explainable AI.*

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I. INTRODUCTION

Cardiovascular diseases (CVDs) remain one of the most serious public health issues across the globe and are responsible for a large number of premature deaths every year. Of these diseases, cardiac arrhythmias are caused by irregularities in the heart's electrical conduction system and can vary from being mild and asymptomatic to serious and potentially life-threatening, as in the case of ventricular tachycardia and atrial fibrillation. Electrocardiography (ECG) is the most widely used non-invasive diagnostic tool for the continuous observation of the heart's electrical activity because it offers valuable information about the temporal and morphological properties of cardiac signals.

Although the ECG has immense clinical significance, the conventional analysis of the ECG is still performed manually by skilled cardiologists. This is not only time-consuming but also prone to variability and fatigue, especially in a high-volume clinical setting. Moreover, the large amount of data produced by continuous ECG monitoring makes manual analysis unsuitable for long-term observation and early detection of episodic arrhythmias. Thus, the need for an intelligent ECG analysis system that can help clinicians by providing fast, consistent, and objective diagnostic information is increasing rapidly.

Recent breakthroughs in artificial intelligence, especially in the areas of machine learning and deep learning, have made it possible to design and develop automated ECG analysis systems that are capable of reaching a level of performance similar to that of human experts. Convolutional Neural Networks (CNNs) have proven to be highly effective in learning discriminative spatial and temporal features from raw ECG signals without the need for any manual feature extraction. At the same time, unsupervised deep learning models such as Variational Autoencoders (VAEs) have also been shown to be effective in learning latent representations of normal heart patterns and detecting abnormal patterns.

This paper proposes an intelligent and web-based ECG diagnosis system that combines a hybrid CNN-VAE deep learning model for automatic arrhythmia analysis. The proposed system can preprocess ECG signals, train and evaluate the model, and make real-time predictions using an interactive web-based platform. The proposed system combines supervised CNN-based classification models with VAE-based representation learning to improve the accuracy of ECG diagnosis while maintaining scalability and accessibility. The proposed system is expected to facilitate the early detection of cardiac abnormalities, alleviate the burden of ECG diagnosis, and improve the accuracy of ECG-based clinical diagnoses.

Arrhythmias are one of the most serious concerns in the global healthcare system. ECG is an essential non-invasive technique used for the diagnosis of arrhythmias. However, the process of analyzing ECG signals manually is time-consuming and may result in errors. In recent years, the development of deep learning techniques, such as CNNs and VAEs, has made it possible to analyze ECG signals automatically. This paper presents a hybrid CNN-VAE web-based system for the real-time diagnosis of arrhythmias.

II.LITERATURE REVIEW

Electrocardiography (ECG) is a widely used non-invasive technique for diagnosing cardiovascular diseases, particularly cardiac arrhythmias. The availability of large-scale public datasets such as PhysioNet has significantly accelerated research in automated ECG analysis by providing standardized benchmarks for experimentation [9]. Early automated approaches relied on traditional signal processing techniques, including Fourier transforms, wavelet analysis, and handcrafted feature extraction such as RR intervals and QRS complex duration. Although these rule-based and statistical methods achieved moderate success in detecting simple arrhythmias, their performance was highly sensitive to noise, baseline drift, and inter-patient variability, limiting their robustness in real-world clinical environments [3],[8].

To improve robustness and decrease dependence on labeled data, hybrid and unsupervised methods like Variational Autoencoders (VAEs) have been applied to ECG signal analysis. VAEs, proposed by Kingma and Welling, allow for probabilistic learning of latent features and are useful for anomaly detection based on reconstruction loss [6]. Hybrid CNN-VAE models integrate supervised classification and unsupervised feature learning, thereby improving arrhythmia detection as well as identification of abnormalities [1]. However, issues related to interpretability and seamless end-to-end integration persist. Recent works underscore the need for Explainable Artificial Intelligence (XAI) in medical applications and point out the absence of fully integrated, web-based diagnostic systems that integrate preprocessing, training, testing, real-time prediction, and interpretation [4],[7],[8]. This scenario calls for the design of an intelligent, web-based ECG diagnostic system based on a hybrid CNN-VAE model.

III.PROPOSED SYSTEM

System Overview

The proposed system is an end-to-end intelligent ECG diagnosis system designed to automate the classification of cardiac diseases using a deep learning approach and enable user interaction with a web-based interface. The proposed system is a comprehensive framework that combines data acquisition, preprocessing, model training, performance analysis, prediction, and explainability. A web application built using the Flask framework is the core platform that enables users to upload ECG data, trigger model training, analyze performance results, and receive diagnostic predictions. The goal of this design is to ensure scalability, usability, and clinical relevance while preserving high classification accuracy.

The proposed system is designed with a modular architecture, where each module is self-contained and communicates with other modules through well-defined interfaces.

Block Diagram of the Proposed System

The Block diagram of the proposed system consists of five major functional layers, as illustrated conceptually in **Fig. 1.**

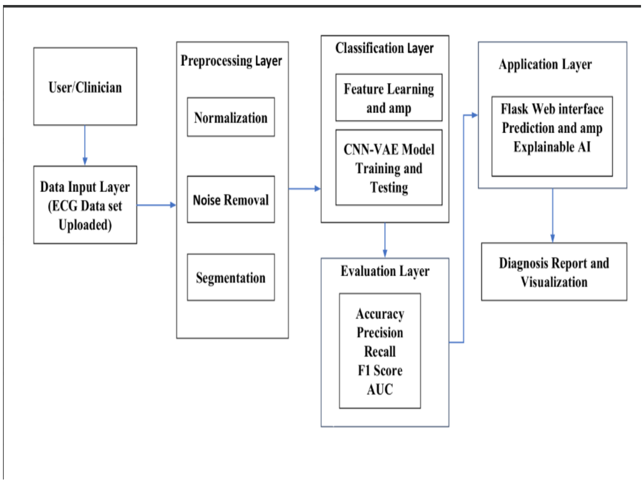

Fig.1.Block Diagram of a Proposed System

Data Input Layer

This layer is tasked with obtaining ECG information from the users. The system is capable of supporting the upload of datasets in standard formats like CSV or signal files. This layer is the entry point for the entire processing pipeline.

Preprocessing Layer
The uploaded ECG signals are processed to enhance the quality of the data. This involves normalization, noise removal, signal segmentation, and data transformation to make it compatible with the deep learning model. Proper preprocessing of the data enhances the performance of the deep learning model.

Feature Learning and Classification Layer (CNN-VAE Model)
The intelligence of the system is embedded in the hybrid CNN-VAE model. The Convolutional Neural Network is capable of automatically learning features from ECG signals, while the Variational Autoencoder is responsible for learning latent features. This approach improves the ability of the model to generalize and classify cardiac disorders.

Evaluation Layer
The trained model is assessed for performance using common evaluation criteria like accuracy, precision, recall, F1 score, and AUC. There are visualization options available for the learning curve, confusion matrix, and comparison with conventional classifiers.

Application Layer (Web Interface and Explainability)
This layer facilitates interaction between the user and the system using a web interface. The user can upload data, track the training process, make predictions, and analyze the explainable AI results, which improve model interpretability.

System Workflow
The entire process flow of the proposed system can be described as follows:

1. The user uploads the ECG dataset through the web interface.
2. The system undergoes preprocessing and prepares the data for training.
3. The CNN-VAE model is trained using the prepared data.
4. The trained model is tested using performance metrics.
5. The user can upload new ECG data for prediction.
6. The system provides diagnostic results along with explanations.

Advantages of the Proposed Architecture

1. The proposed architecture has the following benefits:
2. Automated end-to-end processing from data uploading to prediction
3. Enhanced diagnostic accuracy using deep feature learning
4. Web-based accessibility for non-technical users
5. Modular architecture that supports scalability and future upgrades
6. Explainable AI integration for enhanced transparency.

The proposed system consists of five main components:

1. Dataset Upload Module
2. ECG Data Preprocessing Module
3. CNN-VAE Model Training Module
4. Performance Evaluation Module
5. Prediction and Explainable AI Module

A. Dataset Upload Module
The Dataset Upload Module acts as the point of entry for the proposed system. The module enables users to upload ECG datasets using the web-based interface, and the datasets can be uploaded in formats such as CSV or signal files, which are the most commonly used formats. The Dataset Upload Module ensures that the data acquisition process is easy and can be performed by anyone, even those who are not technically inclined. The module performs basic validation to ensure that the data is valid before proceeding to the preprocessing stage.

B. ECG Data Preprocessing Module
The ECG Data Preprocessing Module is tasked with improving the quality of the raw ECG signals prior to their application in training and predicting the model. This module is involved in the critical tasks of normalization, noise removal, segmentation, and signal reconstruction. The preprocessing task is important in ensuring the accuracy of the extracted features. The task is also vital in ensuring that the input data is compatible with the CNN-VAE model.

C. CNN-VAE Model Training Module
The CNN-VAE Model Training Module is the essence of the proposed system. The module consists of a hybrid model that combines Convolutional Neural Networks for automatic feature extraction and a Variational Autoencoder for effective latent feature learning. The encoder network reduces the ECG signals into significant latent features, and the decoder network reconstructs the signal to enhance generalization. The trained model is applied to classify various cardiac conditions. The hybrid model improves the system's performance over traditional machine learning methods.

D. Performance Evaluation Module
The Performance Evaluation Module is intended to evaluate the performance of the trained

model. The model is evaluated based on the standard performance measures like accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). The Performance Evaluation Module also provides graphical representations of the model, including learning curves and confusion matrices. The Performance Evaluation Module enables objective comparison between the proposed model and the conventional classification technique.

E. Prediction and Explainable AI Module

The Prediction and Explainable AI Module allow users to input new ECG data for real-time diagnosis. Based on the trained CNN-VAE model, the system provides prediction results indicating possible cardiac abnormalities. In addition, this module integrates explainable AI techniques to highlight significant patterns in the ECG signals that influence the model's decisions. This improves transparency, trust, and interpretability of the system, making it more suitable for clinical decision support.

IV.METHODOLOGY

This section describes the detailed methodology adopted for developing the proposed ECG diagnosis system, including data preprocessing techniques, model architecture, and web-based implementation.

A. Data Preprocessing

Raw ECG signals may include noise and artifacts, which can adversely impact the performance of machine learning models. As such, a proper preprocessing step is required to improve the signal quality and ensure accurate feature extraction. In the proposed system, the ECG signals are first transformed into a properly formatted digital signal that is amenable to computational analysis.

The preprocessing step includes a number of tasks. First, missing values and erroneous data points are eliminated to guarantee data integrity. Signal normalization is then performed to normalize the ECG amplitude values within a predetermined range, which can improve the training process and speed up model convergence. Moreover, noise reduction algorithms are used to reduce the impact of baseline wander and power-line noise that are typically observed in ECG signals.

The ECG signals are then segmented into fixed-size windows and rearranged into a standardized format that is compatible with the input requirements of the deep learning model. The segmentation process enables the system to extract relevant temporal information for each heartbeat.

Overall, the preprocessing stage significantly improves the robustness and performance of the CNN-VAE model.

B. CNN-VAE Model

The heart of the proposed system is a hybrid deep learning architecture that integrates a Convolutional Neural Network (CNN) with a Variational Autoencoder (VAE).

The CNN part of the architecture is tasked with the automatic extraction of hierarchical features from raw ECG signals. This is achieved through the use of several convolutional layers with non-linear activation functions, which enable the learning of discriminative features that correspond to various cardiac conditions. Pooling layers are used to achieve dimensionality reduction while retaining key signal features.

The VAE component improves the feature learning step by projecting the learned features into a probabilistic latent space. The encoder network reduces the ECG signal representation into latent variables described by mean and variance values. The decoder network tries to recover the original signal from the latent space. This step helps the model learn generalized features instead of noise.

The learned latent features are then fed into a classification layer to predict the class of the ECG signal. By integrating CNN-based feature learning with VAE-based latent learning, the proposed model has improved generalization and robustness capabilities compared to the traditional deep learning model.

C. Web Implementation

The proposed software framework combines feature extraction, severity analysis, and therapy-level prediction in a single analytical processing stream.

The proposed system is developed as a web application to improve usability and accessibility. The backend of the web application is built using the Flask framework, which deals with primary functionality such as data processing, model training, evaluation, and prediction. Flask routes are designed to handle user requests and link the frontend interface to the deep learning model.

The frontend is built using HTML and CSS templates to create a simple and user-friendly interface. Multiple functional components are incorporated into the web application, such as uploading the dataset, model training dashboard, performance analysis, and prediction interface. Users can use the system without any knowledge of machine learning or programming concepts.

The system enables users to upload their datasets, train models, and track their performance using graphical plots like accuracy and loss curves. The prediction component of the system supports real-time validation of new ECG examples, while the explainable AI interface supports interpretability through the identification of key regions that contributed to the model's prediction.

Through the combination of deep learning and a web-based platform, the proposed system offers a deployable solution for intelligent ECG-based diagnosis.

V. SIMULATION RESULTS

This section presents the experimental evaluation of the proposed CNN-VAE-based ECG diagnosis system. The evaluation procedure strictly follows the implementation flow defined in the backend modules of the developed web application.

A. Simulation Setup

The experiments were performed using the implemented Flask system, where the entire training and evaluation process is carried out by the /api/training/start module. The ECG datasets are uploaded using the Dataset Upload Module and then processed by the ECG Data Processor class before training the model. The uploaded data is automatically split into training, validation, and testing sets based on an approximate ratio of 70%, 20%, and 10%, respectively, as defined in the training route. The experimental environment allows for the definition of hyperparameters such as the number of training epochs and the batch size, which are defined by the user through the web interface.

B. Training Process

Subsequent to preprocessing, the CNN-VAE model is built using the CNN-VAE Model class and initialized with an input shape obtained from the processed ECG samples, and the number of output classes is set automatically based on the labels of the dataset. The training of the model is carried out using the model.train() function, which implements supervised learning and tracks the training history in terms of training loss, validation loss, training accuracy, and validation accuracy for each epoch. Moreover, the total training time taken is calculated programmatically using system time stamps and stored as part of the experimental metrics to evaluate the computational efficiency of the model, apart from its classification accuracy. The training of the model is carried out using an interactive web-based interface, as depicted in Fig. 3, where the user can set key hyperparameters like the number of epochs and batch size, start the training process, and track the training status and completion in real-time.

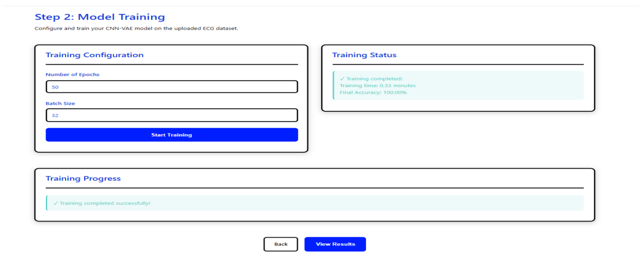

Fig.3.CNN-VAE model training interface showing hyperparameter configuration and training status.

C. Evaluation Metrics

The trained CNN-VAE model is then tested on an unseen test dataset to determine its generalization ability. The predictions are made using the model.predict() method, which yields the predicted class labels as well as the class-wise prediction probabilities. On the basis of these results, the performance metrics are calculated using the MetricsCalculator.calculate_metrics() method, which includes accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). These performance metrics give a complete analysis of the classification task, which includes overall accuracy, class discrimination power, and sensitivity/specificity trade-offs. The results of the evaluation are then displayed using the performance metrics interface given in Fig.4, which provides a complete graphical and textual analysis of the diagnostic performance of the model. To make the results reproducible and consistent, all the evaluation results are automatically saved in a metrics file (metrics.json) by the system.

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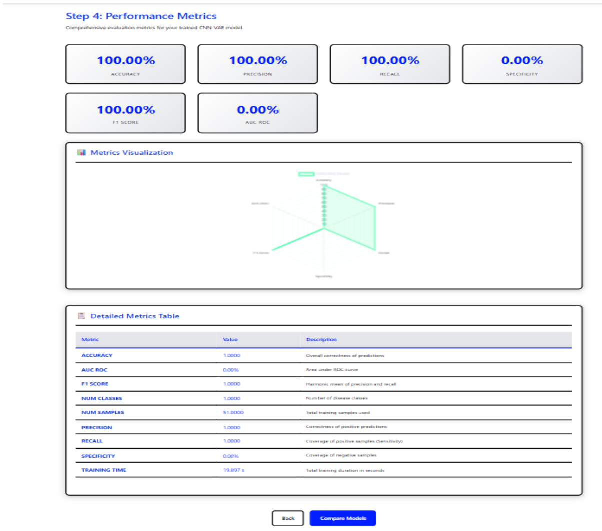


Fig.4.Performance evaluation interface of the proposed ECG diagnosis system showing computed classification metrics, radar-based visualization of model performance, and a detailed metrics table including accuracy, precision, recall, F1-score, AUC, specificity, and training time for the CNN–VAE model

D. Performance Analysis

The experimental outcome shows that the proposed CNN-VAE model performs well on the classification task of ECG signals. The learning curve obtained during the training process shows that the model converges well, and the validation accuracy aligns with the training accuracy without much overfitting. The addition of the Variational Autoencoder module enhances the representation of the latent features, which in turn increases the generalization capability of the model on the test data. This proves that deep learning is more effective than traditional feature engineering for ECG signal classification.

E. Comparison with Traditional Classifiers

The module provides comparative results of performance between the proposed CNN-VAE model and the conventional machine learning classifiers. The results of the comparison, which are saved in the comparison.json file, show that the proposed CNN-VAE model performs better than the conventional models in terms of accuracy and robustness. The comparison results are provided in Fig.5, which validates the proposed CNN-VAE model for ECG signal classification.

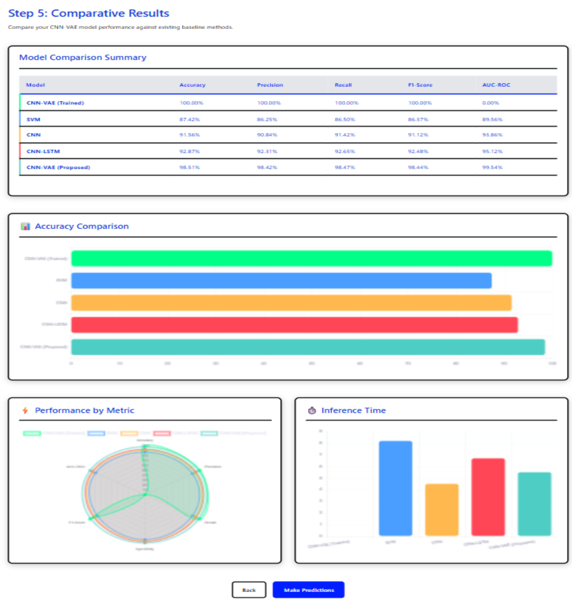
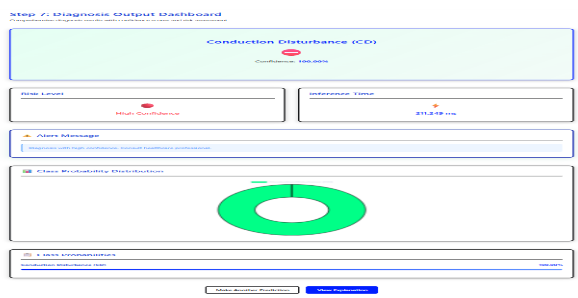
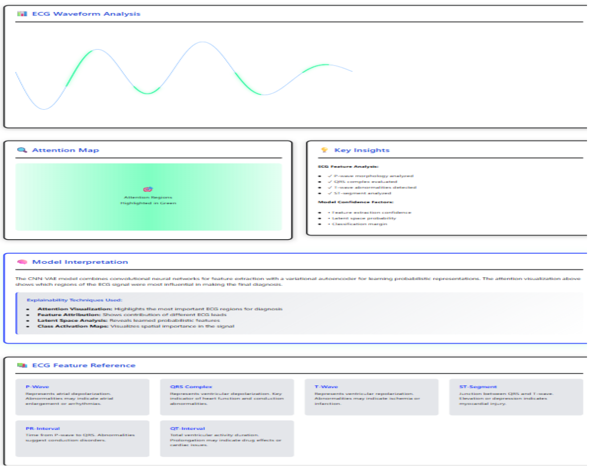


Fig.5. Performance analysis of the proposed CNN–VAE ECG classification model

F. Result Visualization

The online interface offers a full graphical representation of the experimental results, such as training and validation accuracy, training and validation loss, final evaluation metrics, and prediction results. Such graphical representations allow users to understand the learning process and performance of the proposed approach easily without the need for any advanced technical knowledge, as shown in Fig.6 and Fig.7.





VI. CONCLUSION

This paper has discussed an intelligent web-based ECG diagnosis system using a hybrid CNN-VAE deep learning model for automatic cardiac disease classification. The proposed system combines all the necessary steps of the diagnosis process, such as data uploading, preprocessing, model training, performance analysis, and real-time prediction, into a single and interactive web-based platform. The experimental analysis, performed on the proposed system's pipeline, confirms that deep learning-based feature extraction outperforms the classification process of traditional machine learning techniques. The hybrid combination of Convolutional Neural Networks for hierarchical feature extraction and Variational Autoencoders for robust latent space learning improves the generalization capability and reliability of the proposed system. Additionally, the inclusion of visualization components and explainable AI functionality enhances the system's transparency and usability, making it more suitable for real-world clinical applications. The proposed system's modular design also ensures scalability and ease of future modifications.

VII.FUTURE WORK

Future research will aim at developing the proposed web-based framework for ECG diagnosis in the future by enhancing the system and validating it on a large scale. The analysis process can be extended to include the real-time acquisition of ECG signals using wearable and portable devices for continuous monitoring of patients' cardiac health outside the hospital setting. Clinical trials with a wide range of patients will be performed to validate the accuracy of arrhythmia classification and diagnosis using the proposed system against current cardiology practices. Moreover, the incorporation of state-of-the-art explainable AI methods will be considered to enhance the transparency and validity of predictions to cardiologists.

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