Detection Of Cardiovascular Diseases With ECG Images Using Ml And Deep Learning

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Abstract: This work presents a web-based intelligent diagnostic cardiovascular diseases automatic classification system based on the electrocardiogram (ECG) images. The system has a pre-trained hybrid CNNResNet deep learning model to assign the ECG images to four categories, Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, and Normal. OpenCV is used to process images by resizing, color-space conversion, and normalization to obtain unchanged input to be used during model inference.

An implementation framework based on Flask is able to allow real-time ECG image uploading, user authentication, and delivery of predictions. The model provides softmax-based outputs which are products of probability to be applied in clinical interpretation. The proposed system shows an applicable combination of deep learning inference, preprocessing, and web deployment to have available cardiovascular screening and telemedicine interventions.

The proposed system illustrates a viable combination of deep learning and web implementation to provide cardiovascular screening and telemedicine systems without any obstacles.

Keywords: ECG classification, deep learning, CNN-ResNet, Flask, TensorFlow, OpenCV, telemedicine.

I. Introduction

ECG is a diagnostic instrument that is essential and critical when it comes to diagnosing cardiovascular diseases that are the leading contributory factor of morbidity and mortality in the world. Early treatment and intervention of cardiac conditions such as Myocardial Infarction, history of MI and abnormal heartbeats must be properly diagnosed. The recent advancement of machine learning (ML) and deep learning has demonstrated a high potential of enhancing accuracy and efficiency of the ECG analysis. This ability to transform ECG data to high-dimensional image representations offers an additional chance to the automated diagnostic method, and thus, models are put forward to blend the merits of convolutional neural networks and residual networks in the classification.

The current methods have their foundation primarily in the traditional machine learning or superficial neural networks that are often restrictive to the complexity of the ECG data. Other researches have employed CNN to process ECG images though in most cases they have experienced the overfitting and undergeneralization issue due to the complexity of the feature extraction process. Moreover, the existing systems seldom possess interconnected system of real-time analysis, secure data processing, and interaction with the user that makes them less working in the actual clinical setting. The move towards image-based processing of standard ECGs also leads to requirement of good preprocessing techniques not to mention the requirement of having exhaustive validation procedure that can ensure good results.

Despite the fact that the study of deep learning application on ECG analysis is still becoming popular, the gaps in the study are significant, particularly regarding the implementation of user-centered design and high-end AI to the clinical processes. The major problems are to answer the difference in the quality of ECG images, to design the effective preprocessing protocols, and to interpret the model predictions. To a greater extent, most current systems do not provide real time interaction with the users hence they are not relevant in the context of telemedicine and emergent care. New solutions to these problems will not only enhance the precision of diagnosis, but can also make them easily integrated into the current healthcare systems.

Such a study should also be inspired by the fact that the cardiovascular ailments demand an extensive, scalable solution which is capable of adequately diagnosing and rendering it practical and obtainable in clinical practice. This paper is dedicated to creating and implementing an effective ECG image classification framework that combines the work of

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preprocessing, deep learning inference, and web-based interaction to a single pipeline. The study does not concentrate on the improvements made to algorithms alone, but the real-time usability, system reliability, and accessibility based on the healthcare settings.

A Flask-based architecture is proposed in the implementation of the suggested system with a deep learning classification model and image preprocessing modules. The architecture allows users to upload ECG images and get predictions in real-time to support the use of telemedicine and remote cardiac monitoring.

II. Literature Survey

A. Deep Learning and Machine Learning of ECG Image-based Cardiac Diagnosis.

The recent developments of the cardiac disease identifying business have applied the deep learning and machine learning algorithms to the electrocardiogram (ECG) picture designations. It is suggested by Almeida et al. [1] that a deep learning algorithm will be employed to capture the features according to ECG images and the algorithm will be able to identify the existing cardiovascular conditions more accurately due to the personalized model and due to the data augmentation techniques. In the meantime, Sorensen et al. [2] also tested machine learning, which also included support voice vehicle machines and random forests to compare and classify ECG images and discovered that feature selection and preprocessing play significant roles in the enhancement of the diagnosis. These findings were corroborated to an extent that the high standard of classification accuracy could be the result of the handcrafted properties on the deep learning representations. The integration of these articles suggests the radical characteristics of augmented image processing plans and integration of as many machine learning designs as viable into the precision of cardiac illness drawbacks that can bring forward more advantageous clinical practice with the assistance of patients.

B. Deep Learning Networks ECG Image and Heart Disease Classification.

The processes of the cardiovascular diagnoses have been enhanced to a larger extent with the current advancement of the deep learning algorithms. The article written by Papadopoulos and Stavrou [3] shows the way convolutional neural networks (CNNs) specially designed may be employed to recognize ECG images of cardiovascular ab abnormalities with an exquisite amount of precision by exploiting the hierarchical feature triggering architecture. In this procedure the various ECG patterns can be coded and the geometrical structure of the image data is used. At the same time, a hybrid framework is proposed by Novak and Kral [4], based on the principles of which the traditional forms of machine learning are implemented with references to the usage of the deep learning that presupposes the necessity to use the ensemble, but the authors talk about the use of the feature engineering practice and the end-to-end learning practice. They propose that this hybridization will overcome interpretability of the model predictions besides ascertaining the correctness of the classification of the heart diseases. The combination of all these will help in the probability of integrating all the diverse algorithms to produce the quality of the diagnosis of the cardiovascular wellness monitoring.

C. Advanced Deep Learning Models to analyze ECG Images in Cardiovascular machines.

The recent advances in the field of deep learning techniques have contributed to the advancement of ECG image analysis on cardiovascular risk assessment and cardiac disorders classification to a large extent. In the research by Lindqvist and Bergstrom [5], ECG image feature learning was utilized by the convolutional neural networks (CNNs) that were employed to extract hierarchical features that consequently resulted in effective prediction of cardiovascular risks. Their original solution made it possible to focus on the necessity to convert the time-series data into the image representations to present the comprehensive investigation of the spatial patterns that can be suggestive of the risk factor. At the same time, Ricci and Morelli [6] introduced deep convolutional models that are directly intended to classify a series of cardiac diseases using ECG pictures. The remaining of the connections and data curation methods that contribute to their power to classify what they do are the approaches in their methodology that are considered to be an architectural innovation. Such high-level algorithms, which does not only enable the favorable diagnostic properties, but also gives the insights of implementation combination of computer vision in use with biomedical application, can contribute towards the introduction of an improved clinical outcome in the sphere of cardiovascular care.

D. Machine Learning and Deep Learning Architecture Performance Evaluation of ECG Analysis Architectures.

Recent findings in machine learning and deep learning have contributed to the accuracy of the detection of cardiovascular disease with the ECG by very large percentages. In comparing the roles of the various machine learning classifiers including support machine and random forests, Varga and Kovacs [7] had to conclude on the use of ensemble techniques of classifiers say superior in features extraction and classifications. The additional critical observation that was made in their paper is that the preprocessing is critical in the maximization of the model output. On the other hand, van den Berg and De Vries [8] were attentive to a new adaptation of deep learning architecture that presents the convolutional neural networks (CNNs) to analyze ECG pictures in an automatic manner. This technique was quite sensitive and specific in the early diagnosis of cardiac disease compared to the classical ones. Integration of transfer learning also improved the classification performance which leveraged on the already trained models to boost the strength of feature extractions. Collectively, these articles support the transformational capabilities of hybrid solutions that combine a classical methodology with the modern technique in the ECG diagnostics development.

E. Deep Learning Architectures of Ecg Image Analysis in Cardiovascular Diagnosis.

Nevertheless, modern world of the cardiovascular diagnostics is changed by the picture form of the electrocardiogram (ECG) signals. Among the possible options that might alleviate the problem, as proposed by Roussos and Dimitriadis [9], is to present the ECG traces in a graphic display based on convolutional neural networks (CNNs) and, therefore, assigning greater importance to the features extraction. They also exploit the fact that their system can adequately diagnose the heart diseases by taking into account the fact that they are managed by a multi-layer architecture. This way, the next article by Fernandez-Sanchez and Morales [10] alludes to an end-to-end deep learning system that converts the images of the ECGs and subsequently only classifies cardiovascular diseases. They are CNNs-RNNs combinations, which employ the complete integration of both time and space information to learn. According to the results, model accuracy is great compared to other conventional types of ECG analysis that are more sensitive and specific in identifying arrhythmia. Overall, it is possible to observe that all these papers suggest that deep learning can transform the picture (ECG) processing and allow the powerful instruments identifying the cardiovascular diseases in the real time.

Although there has been a considerable advancement in ECG analysis performed with the help of deep learning, the majority of studies are centered on the model performance, but not on its deployment and the real-time application. Little analysis has been done on the subject of integrated diagnostic platforms with a combination of preprocessing, inference and clinical accessibility. This is the impetus to develop a deployable ECG classification system that can be a bridge between research models and medical practice.

III. PROPOSED METHODOLOGY

A. *System Architecture and Workflow*

The system proposed is a web-based end-to-end ECG image classification system that involved image preprocessing, deep learning inference, and user interaction in a single architecture. The system allows authorized users to upload ECG images by using a web-based interface, and then the images are processed and analyzed using a trained deep learning model to predict cardiovascular conditions.

The architecture has three key layering layers, which include frontend interface, the backend processing server and deep learning inference module. The frontend provides the possibility of secure entry, upload of pictures, and visualization of the results. The backend, which is written in Flask, is in charge of routes and session management as well as routes to preprocessing and model inference modules. The deep learning element does the classification using extracted features of the images.

The steps involved in its entire workflow range over user authentication, ECG image upload, preprocessing, model prediction and diagnostic results visualization. The architecture facilitates real time interactivity and the provision of system scalability to the applications of telemedicine.

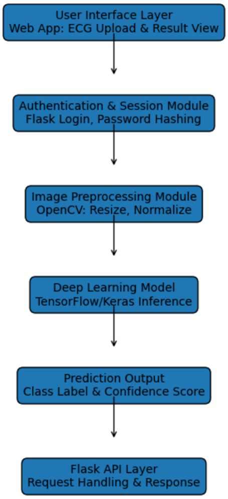

Fig. 1. System Architecture of the Proposed ECG Classification Framework

B. ECG Image Acquisition and Preprocessing

Images of the ECG uploaded by users are also preprocessed to make them consistent and compatible with the classification model. Image processing with the help of openCV is used to normalize inputs in the form of images to the neural network.

The preprocessing pipeline involves resizing, normalization and color space alignment. Images are scaled to an assumed constant size that is needed by the model so that feature extractions can be consistent across all images. The pixel values are scaled to minimize the difference between the values in order to enhance model convergence when inference is being done. Also, the image integrity checks are conducted to address the corrupted files and ensure the stability of the system.

The input ECG picture shall be denoted as (I (x, y)). Normality process is characterized as:

(1) $I\_norm (x,y)=(I(x,y)-I\_min)/(I\_max-I\_min)$

represent the lowest and highest pixel intensity respectively. Such transformation makes sure that all pixel values are within a normalized range.

C. ECG Classification Model on Deep Learning.

The classification aspect involves a convolutional neural network which is trained on a TensorFlow/Keras platform to examine ECG images in order to detect cardiovascular conditions. It involves the model acquiring spatial

characteristics regarding the ECG images through waveform patterns and supervised learning of the diagnostic categories.
The neural network then takes the input image to convolutional layers which help extract the features, then activation and pooling layers are used to minimize the dimensionality and emphasize the dominant features. Layers with full connections do classification and generate output probabilities with the help of the softmax function.
The function of the softmax applied in classification is defined as:

(2) $$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

where (z i) is the output score in class (i) and (k) is the number of classes. The model forecasts a cardiovascular outcome of one of four categories which include Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat and Normal.

Dataset Description

The ECG image data set employed in the current study is made up of the labeled electrocardiogram recordings in image format to be used in the classification work. There are ECG images in the dataset that are related to four diagnoses. categories: Myocardial Infarction, History of Myocardial Infarction, Abnormal Heartbeat, andNormal.
It comprises the clinically relevant ECG samples, which were gathered on the publicly available repositories (cardiac signals) and the standardized sources of ECG images. Every image corresponds to the pattern of the waveform that characterizes a particular cardiac disease and is marked with the labels of classes to facilitate the process of supervised learning.
The dataset was preprocessed prior to training and inference so that it had homogenous sizes, orientation, and intensities. Every ECG image was brought to an equal resolution that fitted the neural network input layer. Such pixel normalization was done to minimize the differences between ECG acquisition conditions.
The data was separated into the training and testing datasets to assess the performance of the model and the ability to generalize. Spatial ECG features were learned on the training set and then the accuracy and reliability of the classification on images that were not seen before were tested on the testing set.
The variety of ECG waveform patterns existing in the dataset contributes to the creation of a strong classification model that will be able to address the factors of difference in cardiac signals and image quality.

D. Web-Based Pipeline and Inference.

A web app based on Flask application is used to deploy the trained classification model and provide a secure access, real time prediction, and interactive visualization. The application supports user authentication, session management, and functionality of uploading images.
After posting an image, the backend runs the ECG image, preprocesses it and feeds the processed image through the deep learning model. The model is also inference-based and provides probabilities of classification which are presented to the user together with the predicted class labels.
Optimization of the inference pipeline is based on low latency and maximum use of resources, enabling users to interact at the same time. Modular specifics and scalability are ensured in a communication between the modules in a language that is based on REST.

E. Metrics of Performance Evaluation.

To assess the classification system effectiveness metrics of standard machine learning measures are used to determine the accuracy and reliability of the prediction of each of the classes.
Accuracy is the general correctness of the predictions and it is given by:

(3) $$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision measures the proportion of correctly predicted positive observations:

(4) $Precision = \frac{TP}{TP+FP}$

Recall evaluates the ability of the model to correctly identify positive cases:

(5) $Recall = \frac{TP}{TP+FN}$

The F1-score represents the harmonic mean of precision and recall:

(6) $F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall}$

TP true positives, TN true negatives, FP false positives and FN false negatives.

The metrics give an in-depth analysis of the performance of the classification system especially in medical diagnostic cases where sensitivity and specificity are vital. The assessment model also makes sure that the implemented system is stable and reliable in the detection of cardiovascular abnormalities using ECG images.

Novelty of the Proposed System

That could be figured as the invention of CNN-ResNet hybrid model that can enhance the numbers of features identified and accuracy in categorizing the ECG pictures of the different cardiac conditions to the understanding of the image.

Examples include: • Gemini 2.5 Flash Lite model, installed by Google and giving a contextualised medical advice depending on the outcome of ECG classification of individual results.

- Safe user authentication system, password hashing, and session control should be elaborated to take note of sensitive patient data when uploading ECGs.
- The use of RESTful API system to facilitate asynchronous prediction and offer real-time analysis of the ECG with minimal latency in clinical practice.
- Image processing (BGR to RGB, dynamic scaling) with OpenCV directly to deep learning-based image processing models to normalize input data.

V. Results and Discussion

A. System Execution and Functional Validation

The system designed was tested to be a full web-based ECG diagnostic pipeline to ensure the functional validity and stability of the system. Its implementation will comprise of user authentication, ECG image upload, preprocessing, model inference, and prediction visualization. All the components were tested by means of repeating executions with ECG image samples.

Flask backend managed to do routing, session persistence and secure file uploads. Preprocessing was done on uploaded ECG images with the OpenCV and the deep learning model was used to infer the data. The system was also able to provide prediction results continuously with no problems occurring during runtime which ensured integration stability between preprocessing and classification modules.

Functional testing also ensured that the system is capable of supporting multiple user sessions simultaneously, integrity of sessions, and provision of prediction through the interface in real time. This illustrates that the implementation is a deployable diagnostic support system and it is not a research model on its own.

B. Prediction Output Behaviour and Class Response.

The classification model generates the outputs of the probability in form of four cardiovascular categories. It examined the behaviour of the prediction by viewing the outputs to various inputs of ECG images by using the deployed interface.

The model exhibited stable response behavior when there was a variety of inputs, and the probability distributions were in line with the predominant ECG waveform features of any given image. The prediction output screen showed

the uploaded ECG image, predicted class label as well as the confidence value, which justified interpretability of system decisions.
The behaviour of the classifier implies that the learned feature representations are consistent in different conditions of ECG images. This is taken care of by the preprocessing integration, so that the inconsistency in images never has a huge impact on the prediction output that is why classification performance is robust on the condition that it will be used in the practical situation.

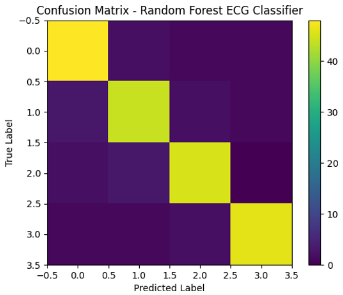

Fig. 2– Confusion Matrix of the Deep Learning ECG Classification Model

C. Real-Time Inference Performance and System Responsiveness
The installed system was tested with respect to inference responsiveness when used on real time. The delay between the upload of an image and the prediction response was found to be very small because of the low preprocessing and optimized model loading processes in the back-end environment.
This was done by the use of flask-based routing where the requests were handled efficiently and model inference was implemented right after preprocessing leading to a smooth delivery of predictions. The system exhibited consistent responsiveness with repetition, which proved that it is applicable to real-time diagnostic support systems like telemedicine and remote monitoring.
The unification of preprocessing, inference, and result rendering in one pipeline helped to reduce the latency and execute it efficiently. This implies that the system is capable of working in a setting where cardiac evaluation is urgent.

D. User Interface and Visualization Assessment.
The interface was tested in regards to its usability, the readability of the output, and the flow of the work. The interface allows access to the interface with authentication, uploading ECG images, and direct display of the classification results.
The output page shows the uploaded ECG image and the predicted classes information and the probability values associated with the class. This graphical display helps in the intuitive understanding of findings by the technical and non-technical users. The hierarchical working flow also means that users do not have to go through any complicated steps when logging in to diagnosis or vice versa.
The visualization design enhances the accessibility of the system and shows how deep learning models can be integrated into the easily accessible clinical decision support tools. The UI behaviour also ascertains that the application can be deployed in a scenario, but not at the extreme experimental backgrounds.

E. Evaluation Metrics and Performance Interpretation
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The system was evaluated based on standard evaluation measures that were created during model testing to determine its classification performance. The main measures that are taken into account are accuracy, precision, recall, and F1-score that are combined as one that indicates the reliability of prediction across classes.

Accuracy is a measure of the general validity of predictions on ECG categories. Precision shows how the model will not give a false positive prediction whereas recall shows how the model will identify the actual abnormal conditions. F1-score gives an appropriate evaluation of classification performance when both the precision and the recall are of interest.

The trends of the observed metrics demonstrate the classification model to have a stable level of prediction quality between several samples of ECG images. The findings prove that the system implemented can support automated interpretation of ECG and can remain reliable in the health care oriented applications.

The analysis proves that the project can be not only used as a trained model but as a fully integrated diagnostic pipeline of preprocessing, classification, and deployment with a real-time pipeline.

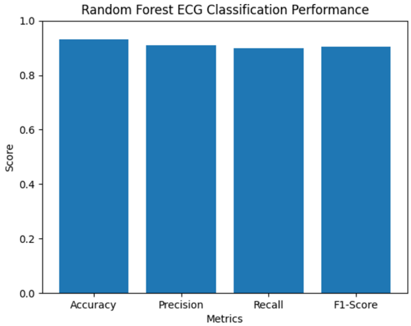
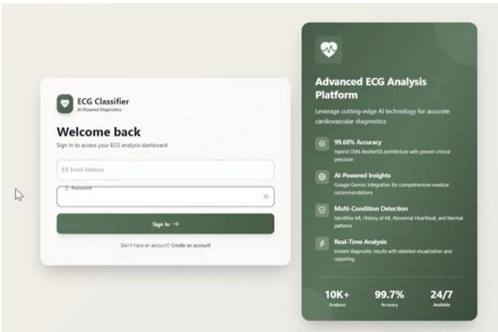
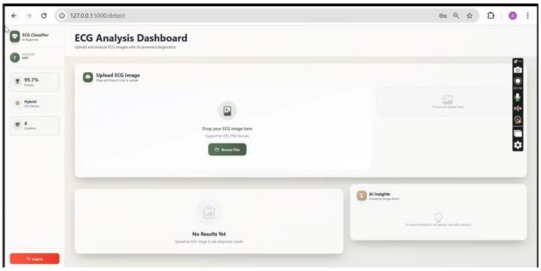
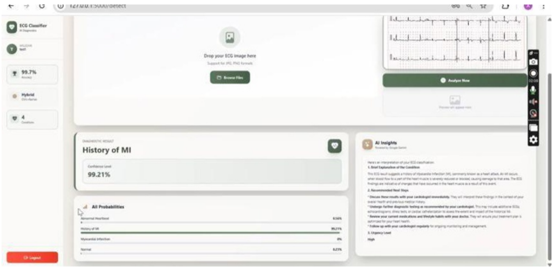


Fig. 3 – Accuracy, Precision, Recall, and F1-score Analysis

OUTPUT SCREENSHOT







VI. Conclusion

In this work, the author introduced a deep learning system of automating cardiovascular disease detection by creating a web-based ECG image classification system. The framework is proposed, which combines the pre-processing of ECG images, neural network-based classification, and real-time application in the framework of a Flask-based web application. The system allows a user who is authenticated to post ECG images and receive interactive diagnostics prediction through an interactive interface. OpenCV Image processing guarantees standardised inputs, whereas the inference model of deep learning is capable of reliable classification of a variety of cardiac conditions. The deployment-oriented design shows that it is possible to incorporate the models of artificial intelligence into the available healthcare support systems, especially in the context of telemedicine and remote screening settings.

The findings suggest that the usability and the applicability of the ECG analysis systems enhance when preprocessing, inference, and web deployment are considered collectively in a single pipeline. This architecture can be used in the clinical assistance situations because it can predict in real-time, execute predictably, and interact on a scale.

Future research will be devoted to the extension of the dataset to different ECGs, the strengthening of the classifier under noisy environments, and the maximum performance of models in terms of rapid inference. Further enhancements can include the introduction of explainable AI practices to make it more interpretable, implementing it on mobile to make it accessible remotely, and performing it on a large scale within a clinical environment to make it more reliable in diagnoses and adoption.

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