Intelligent 12-lead ECG Diagnostic System Development

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Abstract — **Cardiovascular diseases continue to be a leading cause of morbidity and mortality worldwide, emphasizing the critical need for accurate and efficient diagnostic tools. This research paper presents the development of an intelligent 12-lead Electrocardiogram (ECG) diagnostic system leveraging Convolutional Neural Network (CNN) models, specifically the VGG and ResNet architectures. The study utilizes the ECG images from patients diagnosed with both cardiac conditions and COVID-19, comprising a diverse set of ECG images associated with Normal Cardiac Activity, Abnormal Heartbeat, COVID-19, Myocardial Infarction (MI), and Previous History of MI.**

The primary objective of this research is to design a robust diagnostic system capable of classifying ECG images into categories disorder based on ECG waves. The proposed CNN models, VGG and ResNet, will be trained on the dataset to learn distinctive features from the complex ECG waveforms. The research will explore the efficacy of these architectures in capturing intricate patterns and subtle abnormalities present in the ECG images.

The methodology involves preprocessing the ECG images, augmenting the dataset for improved model generalization, and training the CNN models on the labeled dataset. The trained models will then undergo rigorous evaluation using appropriate metrics to assess their performance in terms of accuracy, sensitivity, specificity, and overall diagnostic capability.

The expected outcome of this research is a sophisticated diagnostic tool that can aid healthcare professionals in rapidly and accurately identifying normal cardiac patterns, abnormalities, and potential myocardial disorders from 12-lead ECG images. The conclusions drawn from the final model will provide insights into the effectiveness of VGG and ResNet architectures in this specific medical imaging application and contribute to the ongoing efforts in developing intelligent systems for cardiovascular healthcare.

The findings from this research lay the foundation for future enhancements, including the integration of real-time monitoring capabilities and the expansion of the dataset to further refine and generalize the diagnostic system.

Keywords — Convolutional Neural Networks (CNN), ResNet, VGG, Deep-Learning, 12-lead ECGs, Image Classification, Abnormalities Detection

I. Introduction

Cardiovascular diseases (CVDs) remain a significant global health concern, necessitating innovative approaches for early and accurate diagnosis. Electrocardiogram (ECG) analysis serves as a pivotal diagnostic tool, providing valuable insights into cardiac function. Concurrently, the surge in computer-aided diagnosis based on ECG is transforming the landscape of cardiac health monitoring. The escalating demand for intelligent ECG analysis, driven by advancements in computer technology, necessitates models with higher speed and accuracy.

Despite the technological strides, the development of highly accurate models faces a significant challenge: the scarcity of labeled ECG data. Unlike ordinary target detection data, ECG data is inherently private and challenging to collect and annotate. Expert annotation by electro-cardiology specialists using professional annotation software is required, contributing to the shortage of labeled data and impeding the progress in ECG intelligent analysis.

Over the past decades, considerable research efforts have been dedicated to computer-assisted electrocardiographic diagnosis, yielding commendable results. Arrhythmia detection based on heartbeat categorization has proven effective in various clinical scenarios, encompassing normal beats, supraventricular ectopic beats, ventricular ectopic beats, fusion beats, and unknown beats. Common arrhythmias, including atrial fibrillation, cardiac ischemia, myocardial infarction, ventricular fibrillation, and ventricular tachycardia, have been successfully diagnosed using traditional methods relying on feature extraction and pattern recognition.

In this context, deep learning techniques, particularly Convolutional Neural Networks (CNNs), presents a promising avenue for the development of intelligent diagnostic systems. With the advent of CNNs, researchers are exploring more end-to-end learning approaches to pattern recognition in ECG. While deep learning models exhibit remarkable performance, they come at the cost of a substantial demand for labeled data. The current limitations in data labeling hinder the progression of computer-assisted ECG diagnosis.

This paper proposes an intelligent approach to address the labeled data shortage by introducing a deep learning model for ECG detection. By combining deep learning and active learning, this model aims to retain the high-performance advantages of deep learning while significantly reducing the dependence on labeled data. This section provides an overview of the motivation behind the research, the significance of leveraging deep learning in ECG diagnostics, and the specific objectives of the study. The subsequent sections delve into related work, the proposed method, the selected database, data preprocessing, experimental results, and conclude with insights into the potential impact of this innovative approach on the field of ECG intelligent analysis.

II. RELATED WORK

A. Deep-Learning Methods applied to the ECG

The literature on deep learning [1] underscores its role in transforming machine learning by using neural networks with multiple layers to autonomously learn complex representations from input data. Traditional models, such as linear regression, relied on human-selected features, limiting their adaptability. In contrast, deep-learning networks, particularly Convolutional Neural Networks (CNNs), excel in representation learning by autonomously extracting features without human intervention.

CNNs, initially designed for computer vision, utilize convolutional filters to extract relevant features from input data. Unlike traditional models, CNNs learn both the representation of data and the rules governing this representation during self-training. In the context of electrocardiogram (ECG) analysis, CNNs interpret ECG signals along spatial and temporal axes, allowing for horizontal, vertical, or combined convolutions. This approach eliminates human bias, reduces dependence on expert feature engineering, and accommodates the complexities of ECG waveform analysis.

While the agnostic approach of neural networks achieves optimal representation, it also introduces non-linearity and opacity in the learned associations between input and output, rendering the model a "black box." This lack of interpretability raises concerns, particularly in clinical applications. In contrast, less agnostic machine-learning models, such as logistic regression, reinforcement learning, and random forest models, maintain interpretability and hold promise for informing research and clinical practice.

Reinforcement learning, a subfield of artificial intelligence, offers a framework for training clinical decision models by associating decisions under specific conditions with long-term outcomes. Additionally, unsupervised machine-learning methods, like clustering models, mitigate the risk of error introduced by human labeling during training. This Review also extends discussions to natural language processing applications, which integrate AI, computer science, and linguistics to structure unstructured clinical data, such as free text in electronic health records, through methods like rule-based recognition, text vectorization, and topic modeling. The integration of these approaches underscores the evolving landscape of intelligent analysis in diverse medical domains.

B. Deep Neural Network Model

The deep network model [2], implemented using PyTorch, employed Convolutional Neural Networks (CNNs) for both digital signal (CNN-dig) and image (CNN-ima) identification. While CNNs are typically applied to images, adjustments were made to the network architecture and convolution kernel size for spatial and temporal feature extraction in ECG signals. Stacked blocks of convolutional, batch normalization, and dropout layers were used, and different architectures were applied to short and long ECG leads. The CNN-ima took RGB color images as input, while the CNN-dig processed digital signal data. Hyperparameters, such as batch size, learning rates, and convolution kernel sizes, were adjusted to optimize model performance. The network depth was optimized to balance the number of trainable parameters, deep learning capabilities, and dataset size.

The training process involved Adam optimization with binary cross-entropy loss functions. The resulting models achieved high detection accuracy for various cardiac conditions. This study contributes to the field by providing insights into the architecture and optimization of deep neural networks for ECG signal analysis, showcasing their applicability in medical diagnostics.

III. METHODOLOGY

In this study, we employed Convolutional Neural Networks (CNNs) as the primary computational framework for the classification of Electrocardiogram (ECG) data images. Specifically, two well-established CNN architectures, VGG (Visual Geometry Group) and ResNet (Residual Network), were implemented to discern patterns indicative of cardiac conditions. The choice of these architectures is motivated by their proven effectiveness in image recognition tasks.

A. Data Collection

The study encompasses a dataset comprising ECG images from patients diagnosed with both cardiac conditions and COVID-19 [3]. This unique dataset includes 1937 distinct patient records, gathered using the 'EDAN SERIES-3' ECG Device deployed in Cardiac Care and Isolation Units [3] across various healthcare institutions in Pakistan. Medical professors, operating within Telehealth ECG diagnostic systems and supervised by experienced professionals in ECG interpretation, conducted a meticulous manual review of the collected ECG images data. This comprehensive reviewing process spanned several months, covering five distinct categories: COVID-19, Abnormal Heartbeat, Myocardial Infarction (MI), Previous History of MI, and Normal Person.

12-lead based standard ECG images [4] collected from distinct patients do not contain any personal information about the patient. Below this paragraph, Table 1 reports the number of images for the different cases. This dataset encompasses a diverse range of ECG images representing normal cardiac activity, abnormalities, and myocardial disorders [4].

Sr.	Category / Folder Name	No. of Distinct ECG Images	Sample Rate	Leads
1	COVID-19 Patients	250	500 Hz	12 – Leads
2	Normal Person ECG Images	859		
3	Myocardial Infarction Patient	77		
4	Patients with Previous History of Myocardial Infarction	203		
5	Patients with Abnormal Heartbeat	548		

Table 1: Dataset Overview

1) COVID-19

The COVID-19 (Coronavirus) surfaced in late December 2019 in the city of China and swiftly spread worldwide [4][5]. Most individuals affected by the COVID-19 virus may exhibit symptoms such as shortness of breath and respiratory issues, and recovery may occur with or without specific treatment.

2) Normal Person

A normal person [6] in medical terms is a person that is functioning normally, without any observable abnormalities.

3) Myocardial Infarction

Myocardial infarction (MI) commonly known as a heart attack, occurs when the flow of blood decreases or stops to a part of the heart, causing severe damage to the heart. Most common symptom is chest pain or discomfort which may travel into the shoulder, arm, back, neck, or jaw. MI is a type of acute coronary syndrome, which describes a sudden or short-term change in symptoms related to blood flow to the heart and it can be detected by Electrocardiogram (ECG) sensing for proper diagnosis of the patient [4][7].

4) Previous History of Myocardial Infarction

Patients that are recently recovered from Myocardial Infarction (MI) or Heart Attack.

5) Abnormal Heartbeat

ECG images of the Patients that are suffering from Abnormal Heartbeat recently recovered from COVID-19 and Myocardial Infarction and have symptoms of shortness of breath or respiratory illness[4].

B. Methods

Convolutional Neural Networks (CNNs) are employed due to their exceptional ability in pattern recognition and feature extraction from complex visual data, such as Electrocardiogram (ECG) images. CNNs are particularly well-suited for image-based tasks, and in the context of ECG analysis, they offer the capacity to discern subtle cardiac patterns indicative of various conditions. Leveraging the deep-layered architecture of CNNs, this approach aims to enhance the accuracy and efficiency of classifying ECG images, enabling robust detection of cardiovascular abnormalities, including conditions like myocardial infarction, normal or abnormal heartbeats. The utilization of CNNs aligns with the project's objective of developing a reliable and effective diagnostic tool for healthcare institutes focusing on cardiac health and, specifically, COVID-19-related cardiovascular implications.

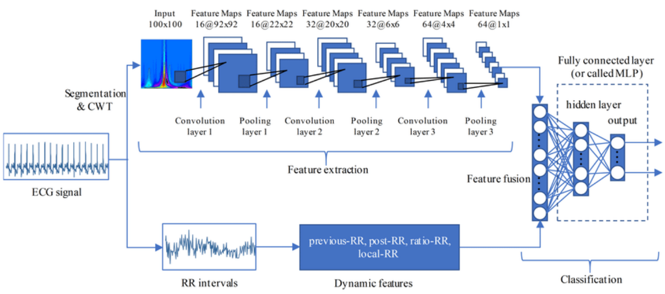

Figure 1: CNN Model Architecture [8]

1) VGG

One of the models that we adopt in this project is the VGG (Visual Geometry Group) architecture to tackle the classification of Electrocardiogram (ECG) images into five distinctive categories. VGG is a convolutional neural network (CNN) architecture recognized for its straightforward and uniform structure, comprising stacked convolutional layers with small kernel sizes. The VGG model's depth and homogeneity contribute to its efficacy in learning hierarchical features within image data. Applied to ECG images, VGG is expected to excel in capturing relevant patterns and discriminative features crucial for accurate classification.

The research evaluation process involves dataset division into training, validation, and test sets, preprocessing steps tailored for optimal model performance, and hyperparameter tuning to fine-tune the model's learning capabilities. Evaluation metrics such as accuracy, precision, recall, F1 score, and confusion matrix are employed to assess the model's performance comprehensively.

The final validation occurs on an independent test set, with potential refinements based on observed outcomes. Interpretation of results underscores the significance of incorporating domain-specific knowledge and collaborating with medical professionals to ensure the clinical relevance and robustness of the proposed VGG-based model for ECG classification.

2) ResNet

In this research, we employ the ResNet architecture as our second model, a deep learning framework renowned for its effectiveness in addressing the challenges of training deep neural networks. ResNet is a type of CNN architecture that is also used for the classification of images. Leveraging the residual learning concept, ResNet facilitates the training of exceedingly deep networks by utilizing shortcut connections that skip one or more layers. This enables the model to learn residual mappings, mitigating issues such as the vanishing gradient problem and enhancing the extraction of intricate features from ECG images.

The anticipated results include enhanced accuracy in capturing both low-level and high-level patterns within the ECG data (P-QRS-T points). The evaluation process is the same as for the previous model: data splitting into training, validation, and test sets, preprocessing steps, hyperparameter tuning, and the utilization of metrics such as accuracy, precision, recall, F1 score, and confusion matrix. The results are visually presented and compared with VGG.

C. Evaluation Metrics

At the end, as part of the evaluation metrics, we compare the performance of ResNet and VGG architectures and their results. Key metrics, including accuracy, precision, recall, F1 score, and confusion matrices, are employed to gauge the efficacy of each model. These metrics provide a comprehensive assessment of the models' classification capabilities, considering factors such as overall correctness, precision in identifying true positives, recall in capturing relevant instances, and the harmonic mean of precision and recall (F1 score).

By contrasting the outcomes of these metrics for both ResNet and VGG, we aim to discern the relative strengths and weaknesses of each architecture in the context of ECG image classification, contributing valuable insights to guide model selection for this specific medical application. Furthermore, models are going to be trained and adjusted for more precise outcomes and capturing more features.

IV. Conclusion

This research has investigated the application of ResNet and VGG architectures for the classification of ECG images into five distinct categories. Both models demonstrated promising capabilities in capturing intricate patterns inherent in ECG data points. The evaluation metrics facilitated a thorough comparison of their performances. The results revealed nuanced differences in the strengths and weaknesses of ResNet and VGG in the context of ECG classification. ResNet, with its residual learning approach, showcased notable advantages in handling the depth of the neural network, while VGG, with its uniform structure, demonstrated commendable performance in feature extraction. The choice between these architectures should be made based on the specific requirements of the ECG classification task, considering factors such as interpretability, computational efficiency, and clinical relevance. This research contributes valuable insights to the field of medical image classification, aiding practitioners, and researchers in selecting an appropriate deep learning architecture for ECG analysis. Further investigations and refinements could enhance the applicability of these models in real-world clinical settings.

V. Figures and Tables:

Table 1: Dataset Overview; Dataset is covering five distinct categories: COVID-19, Abnormal Heartbeat, Myocardial Infarction (MI), Previous History of MI, and Normal Person [4]

Figure 1: CNN Model Architecture; CNN architecture; Convolutional Neural Network (CNN) not only uses the CWT scalogram of heartbeat, but also adopts the RR interval features. [8]

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