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Cardiovasular Disease Detection Using ML and DL

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A B S T R A C T

Cardiovascular diseases are a leading cause of death globally, and early detection plays a key role in improving patient outcomes. This project presents a deep learning-based approach to detect heart diseases from ECG images using a convolutional neural network (CNN). The system takes ECG images as input, performs preprocessing steps like grayscale conversion and lead extraction, and classifies the condition using a fine-tuned ResNet-18 model. A user-friendly interface is developed using Streamlit that supports image uploads, live camera input, and role-based login for doctors and patients. The system demonstrates high prediction accuracy and can be enhanced further for clinical use.

Keywords:ECG, Heart Disease, CNN, ResNet-18, Deep Learning, Streamlit, Image Processing

1. Introduction

Cardiovascular diseases (CVDs) represent the leading cause of death worldwide. The World Health Organization estimates that 17.9 million people die from CVDs annually. Among various diagnostic tools, the electrocardiogram (ECG) plays a pivotal role in clinical practice. It is a simple, non-invasive, and cost-effective method for recording the electrical activity of the heart. Traditionally, trained cardiologists interpret ECGs; however, human analysis is prone to fatigue, inter-observer variability, and relies on expert knowledge that may not always be accessible. Artificial intelligence (AI) offers promising solutions to mitigate these limitations. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), enable the automatic analysis of ECG images and the detection of abnormalities with high accuracy. This project utilizes a fine-tuned ResNet-18 model to classify ECG images into four distinct categories: Normal, Abnormal Heartbeat, History of Myocardial Infarction (MI), and Active Myocardial Infarction. By integrating this model into an interactive web application using Streamlit, users can upload ECG images, visualize the preprocessing steps, and obtain real-time predictions regarding potential heart conditions.

2. Problem Statement

The manual interpretation of ECG images is a time-consuming process that demands specialized expertise. In rural and underserved areas, access to cardiologists is often limited. Moreover, early-stage symptoms might be overlooked by non-specialists. Consequently, there is a critical need for an accessible, rapid, and accurate system to assist or even automate heart disease detection from ECG images. The primary aim of this project is to develop an AI-powered diagnostic system capable of analyzing ECG scan images using a deep learning model and providing predictions about potential heart conditions. The solution should be accurate, interactive, and user-friendly, rendering it suitable for both clinical and remote healthcare applications.

3. Objectives

The objectives of this project are as follows:

- To preprocess ECG images and extract meaningful signals.

- To train and fine-tune a deep learning model (ResNet-18) for classifying ECG images into Normal, Abnormal Heartbeat, History of MI, and Active Myocardial Infarction.
- To develop an interactive web application that allows users to upload ECG scans and receive diagnostic predictions.
- To implement login and registration functionalities for doctors and patients, providing personalized access to the system.
- To visualize each step of the ECG image processing pipeline to enhance the explainability of the model's predictions.

4. Literature Survey

Several studies have employed AI techniques for interpreting ECG data. Rajpurkar et al. (2017) demonstrated cardiologist-level arrhythmia detection using CNNs. Hannun et al. (2019) advanced this by classifying various cardiac conditions using a single-lead ECG dataset. Other researchers, such as Attia et al. (2019), applied deep learning to predict ejection fraction from ECGs, showcasing the versatility of AI in cardiology. However, a majority of these systems utilize raw ECG signal data rather than images. This project aims to address this gap by focusing on ECG images, which are more commonly available in printed or scanned formats, particularly in low-resource settings.

5. Methodology

The methodology encompasses dataset selection, image preprocessing, model training, user authentication, and web application development.

5.1. Dataset

The model is trained on the PTB-XL dataset and augmented with ECG image datasets, such as those available from Mendeley Data. These images represent 12-lead ECG scans annotated with medical diagnoses. The images are categorized into four diagnostic labels:

- Normal
- Abnormal Heartbeat
- History of MI
- Myocardial Infarction

5.2. Preprocessing

The image preprocessing pipeline includes several steps:

- **Grayscale conversion:** To simplify and reduce color-related noise.
- **Segmentation:** The image is segmented into 12 regions, each corresponding to one of the 12 leads.
- **Waveform Extraction:** Waveform signals are extracted from each segment using contour detection and morphological operations.
- **Signal Conversion:** Extracted signals are converted to 1D arrays and organized into a structured DataFrame. This preprocessing enhances the quality of data fed into the deep learning model and aids users in visualizing ECG signal patterns. *(Figures illustrating these steps would be embedded here, with captions below each figure)*

5.3. Model Training

A ResNet-18 architecture is employed, selected for its balance between performance and training efficiency. The model is fine-tuned using transfer learning:

- The final fully connected layer is modified to output 4 classes (Normal, Abnormal Heartbeat, History of MI, Myocardial Infarction).
- Cross-entropy loss is used as the loss function, with the Adam optimizer for training.
- The model is trained on augmented ECG images to improve its generalization capabilities.
- The trained model is saved as `best_model.pth` and subsequently loaded into the web application for inference. *(Equations, if any, would be typed in Mathtype and numbered on the right)*

5.4. User Authentication

A basic login and registration system is implemented using Streamlit's session state management. Two user roles are defined:

- **Doctor:** Can access patient uploads, review diagnostic results, and log out.
- **Patient:** Can upload their ECG scans and view their own results. User credentials are currently stored in a local dictionary; this can be upgraded to a secure database in future iterations.

5.5. Web Application (UI/UX)

Streamlit is utilized to create a fully interactive user interface:

- **Home Tab:** Provides a project description, information about the AI model, and usage instructions.
- **Disease Detection Tab:** Features a file uploader or camera input for ECG images, step-by-step visual feedback on preprocessing (grayscale conversion, segmentation, waveform extraction), and the final prediction results. The interface is designed to be responsive, clean, and professional, emulating a basic telemedicine dashboard.

6. Results and Evaluation

The model achieves high accuracy in predicting the correct class for ECG images. The output provided to the user includes:

- The predicted class (e.g., Myocardial Infarction).
- The model's confidence level for the prediction, expressed as a percentage.
- A breakdown of probabilities for all four classes, enhancing transparency. Users can validate the predictions with visual cues from the displayed ECG leads and waveform plots. The incorporation of explainable AI (XAI) elements, such as lead-wise plotting and tabular signal data, makes the model output understandable even to non-technical users. *(Tables summarizing results would be embedded here, with captions above each table)*

7. Applications

The developed system has several potential applications:

- **Remote Diagnosis:** Can be deployed in rural clinics or areas where specialist cardiologist access is limited.
- **Clinical Triage:** Assists healthcare professionals in prioritizing emergency cases based on real-time ECG evaluation.
- **Medical Training:** The visual pipeline can serve as an educational tool for medical students and professionals learning ECG interpretation.
- **Health Kiosks:** Can be integrated into public health kiosks in pharmacies, metro stations, or community centers to provide instant cardiac health screening.

8. Limitations and Future Enhancements

8.1. Limitations

- The system currently processes static ECG images; support for dynamic, real-time ECG signal input is not yet integrated.
- Data imbalance, common in medical datasets, may introduce bias towards more frequently occurring classes.
- The current user authentication mechanism is basic and requires integration with a secure database and encryption for production deployment.

8.2. Future Improvements

- **Real-time ECG:** Support real-time ECG data acquisition via IoT devices.
- **Explainability:** Implement advanced XAI tools like Grad-CAM to provide deeper insights into model decisions.
- **Reporting:** Add functionality for generating PDF summaries of diagnostic reports.
- **Integration:** Integrate the system with hospital Electronic Medical Record (EMR) systems for automated data storage and retrieval.
- **Accessibility:** Enhance the UI with multilingual support and voice-guided navigation for improved accessibility.

9. Conclusion

This project successfully demonstrates the application of deep learning to address a critical healthcare challenge: heart disease detection using ECG images. By combining a fine-tuned ResNet-18 model with an interactive and visually intuitive web application, the system empowers both doctors and patients to perform cardiac screening with greater ease and accessibility. While this tool is not intended to replace medical professionals, it serves as a valuable diagnostic aid, particularly in remote or resource-constrained settings. The project bridges the gap between AI research and practical clinical utility, laying the groundwork for more advanced intelligent healthcare systems in the future.

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