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Enhancing Arrhythima Diagnosis Through ECG Deep Learning Classification Deployment and Agumented Reality 3D Heart Visualization

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Abstract: Cardiovascular diseases (CVDs) are still one of the leading causes of mortality worldwide, which reveals the importance of early and precise diagnosis. ECG stands for electrocardiography and is a helpful diagnostic tool that allows doctors to identify and track different heart conditions by examining the electrical activity of the heart. However, manual identification of ECG features and classification of heartbeats is a time consuming and difficult task which requires a lot of skills. We developed a novel system named ArythmiAR to solve the above problem by integrating Convolutional Neural Network (CNN) and Augmented Reality (AR) for interactive diagnosis with 3D visualisation and real-time interaction. The main features of the ArythmiAR are: (1) deep learning ECG classification for efficient arrhythmia detection; (2) 3D heart modelling and assembly for better visualisation; (3) AR interface for deploying CNN models; (4) 3D location of the sub-regions of the heart responsible for arrhythmia anomalies; and (5) improved 3D visualisation and interaction. In this work we explore different ECG classification approaches, using data rebalancing techniques to improve the performance of the models. Our focus is on Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) models that performed very competitively on PhysioNet MIT-BIH Arrhythmia dataset and reached 99.07% accuracy with MLP model. The work also demonstrates the use of the deep learning model for ECG classification in an AR environment. It is a prototype for augmented rendering, allowing the user to locate, see and interact with specific parts of the heart that cause arrhythmia. The platform gives doctors the tools they need to make better diagnoses and create better treatment plans, improving care for all patients.

Keywords— ECG Classification, Arrhythmia Detection, Deep Learning, Convolutional Neural Networks (CNN), Multilayer Perceptron (MLP), Augmented Reality (AR), 3D Heart Visualization, Medical Imaging, Healthcare AI, PhysioNet MIT-BIH Dataset.

I.INTRODUCTION

[1] Cardiovascular diseases (CVD) remain the leading cause of death globally, accounting for almost one-third of all deaths annually. Early and accurate diagnosis of these diseases is important for better patient outcomes, lower healthcare costs, and prevention of serious complications.[12] One of the most popular methods for checking the electrical activity of the heart and for detecting abnormal rhythms is still electrocardiography (ECG). ECG signals provide important information about arrhythmias, ischaemia and other heart problems.[7] Manual interpretation of an ECG is important for doctors, but it can be time-consuming, error-prone and requires a lot of knowledge. The increasing number of CVDs demands automated intelligent diagnostic systems for the quick analysis of ECG signals to assist doctors in decision making. [6]The advent of artificial intelligence (AI), machine learning (ML) and deep learning (DL) have brought significant improvements to automated ECG classification. Convolutional Neural Networks (CNNs) have been shown to be quite adept at learning hierarchical features directly from raw ECG signals, without requiring much feature engineering.[2] At the same time, visualisation technologies such as Augmented Reality (AR) have become powerful tools in medical diagnostics and education, providing immersive, real-time interaction with anatomical models. But their use in deep learning-based ECG classification is largely unknown. To address this gap, we propose a novel platform called ArythmiAR, that combines CNN-based arrhythmia detection with AR-enabled 3D visualisation of the heart.[13] ArythmiAR not only classifies ECG signals with high accuracy, but also provides doctors with an interactive 3D visualisation of heart areas related to arrhythmia. This aids diagnosis, learning and better treatment planning.”[3]

II. RELATED WORK

Recent studies have shown significant progress in automatic detection of arrhythmia using deep learning approaches. [8]Traditional ECG analysis methods such as the Pan-Tompkins algorithm are rule-based signal processing methods and require manual feature engineering. That makes them less flexible in terms of different data sets and patient conditions.” Nowadays, Convolutional Neural Networks (CNNs) are widely adopted to classify ECG signals due to their ability to automatically identify hierarchical features in raw data .[4] Rajpurkar et al.[9] developed a deep learning model capable of detecting arrhythmias with cardiologist-level accuracy. This is one way AI could be used for medical diagnosis. The deep neural network system for detection of different types of heart rhythm problems, developed by Hannun et al., was also shown to generalise well over a wide range of ECG datasets. Acharya et al. also worked on CNN-based heartbeat classification and proved that it is helpful in classifying different types of arrhythmia.[5] [14] AI based methods have also been a great interest in medical visualisation and training and also Augmented Reality (AR). With augmented reality (AR), you can see and manipulate anatomical structures in 3D, which makes medical education more appealing and easier to comprehend. But most AR systems today only display static images and don’t work with smart diagnostic systems.[10] Recent studies have investigated the combination of AI and AR for healthcare applications. However, there is a major gap in integrating real-time ECG classification with interactive 3D visualisation of cardiac anatomy. System latency, hardware limitations and problems of real-time processing are still unsolved.[11] The proposed ArythmiAR system addresses these problems by using deep learning for ECG classification and augmented reality for 3D heart images display. The integrated approach leads to better accuracy in diagnosis, ease of understanding and user interaction, making it a complete solution for modern cardiac healthcare systems.[15]

III. METHODOLOGY

The methodology aims at developing an intelligent system by combining deep learning based ECG classification and augmented reality to enhance the arrhythmia diagnosis. There are many steps in the method such as getting data, cleaning data, finding features, training the model, adding AR and testing its performance.

First, ECG data are obtained from reliable databases like the PhysioNet MIT-BIH Arrhythmia database. The recorded signals are preprocessed in several ways, e.g. noise filtering, baseline correction and segmentation into single heartbeats. Class imbalance problem is addressed by applying techniques for data balancing such as oversampling and undersampling.

In the next step the vital information is obtained from ECG signals such as the shape of the waveforms and the time characteristics. The processed dataset is then used to train deep learning models like Convolutional Neural Networks (CNN) and Multilayer Perceptron (MLP) to classify different types of arrhythmias. Some of the ways to enhance the models are hyperparameter tuning, dropout regularisation and cross validation.

The classification results are projected onto a 3D heart model after training of the models. This mapping allows us to identify specific areas of the heart that are associated with identified arrhythmias. The system then projects these results in an augmented reality environment, where the user can see and manipulate in real-time the heart model.

In the end, the system is evaluated by performance metrics such as accuracy, precision, recall and F1-score. Experimental results show that the proposed method performs well in terms of high classification accuracy and fast system performance.

IV. SYSTEM ARCHITECTURE:

The system architecture is designed as a hybrid framework over data processing, deep learning and augmented reality technologies. It has many layers such as data acquisition, pre-processing, classification, visualisation and user-interaction.

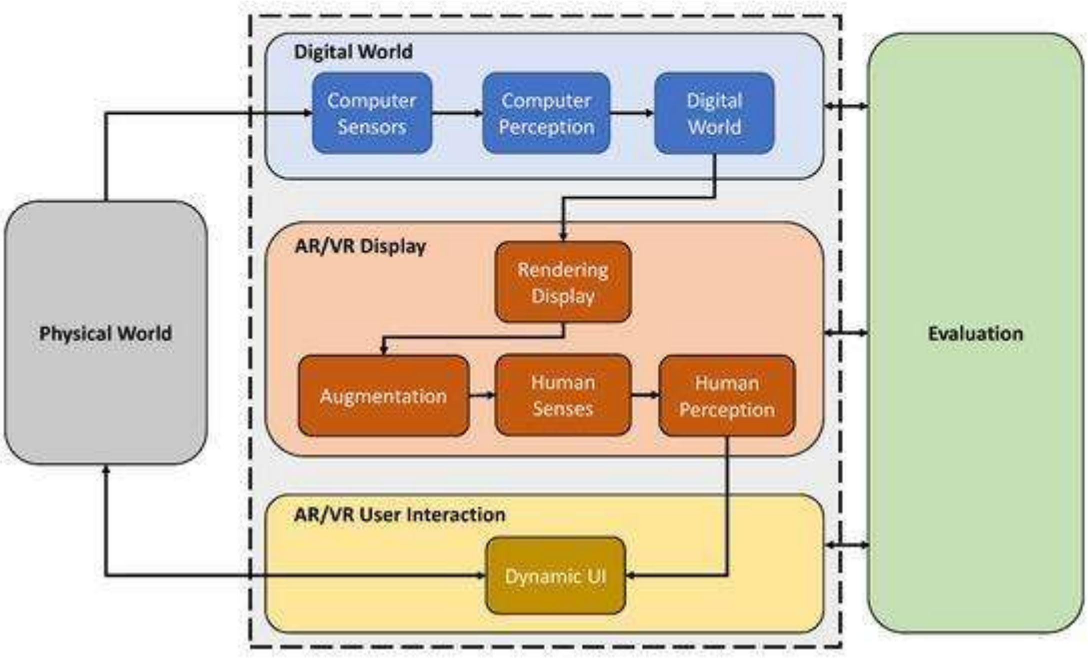
The data acquisition layer gathers ECG signals from datasets or real-time monitoring devices. The preprocessing layer clears and normalises the data to provide good quality input to train the model. The classification layer uses deep learning models like CNN and MLP to classify the arrhythmias.

The visualisation layer projects the classification results to a 3D model of the heart, allowing for a spatial understanding of the cardiac abnormalities. The AR interface adds to the diagnosis an immersive experience in which the user can interact with the 3D model in real time. The system also has modules for authentication, reporting and decision support.

A. overview:

The ArythmiAR system offers a novel approach for cardiac diagnosis by combining the deep learning and augmented reality technologies. It allows automated ECG classification with high accuracy and interactive 3D visualisation of the heart's anatomy. The integration improves diagnostic accuracy, increases user engagement, and allows for better clinical decision making.

B .System Architecture:



V. EXPERIMENTAL SETUP:

The experimental design aims to evaluate the performance of the ArythmiAR system in real-life situations. The system uses ECG datasets from the PhysioNet MIT-BIH Arrhythmia database which has labelled heartbeat signals that can be used to train and test deep learning models. It is preprocessed by noise filtering, normalisation and segmentation methods for ensuring high quality data for model training.

The implementation is performed on a standard computer with Python, TensorFlow and other deep learning libraries. The system is designed on a web framework with Django, which has the ability to connect to AR visualisation modules and user interfaces. Optimised settings, such as batch processing, dropout and cross-validation, are used for training the CNN and MLP models.

We do a lot of experiments to test how well the system works. These include the accuracy of the classification of the arrhythmia, the response speed of the system, and the performance of the model. The AR module is tested to see if it can interact in real time, meaning that it can display the 3D heart model smoothly and accurately map any abnormalities it finds. We check the system's working with performance metrics such as accuracy, precision, recall, and F1-score.

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VI. RESULT AND DISCUSSION:

The experimental results show that the ArythmiAR system with deep learning models has a high accuracy to find the arrhythmias. The Multilayer Perceptron (MLP) model gets accuracy up to 99.07% and the CNN model also captures the patterns in ECG signals well.

The system successfully combines classification outputs with augmented reality visualisation, offering users the ability to interact with a 3D heart model and visualise arrhythmia-related problems. Interaction with the AR interface is easy and responsive increasing the user experience and the understanding of the diagnosis.

The system also handles class imbalance well using data rebalancing methods, enabling both common and rare arrhythmias to be detected reliably. The proposed system is performing well due to its high accuracy, fast processing and interactive visualisation.

A. Results table:

S.No	Data Size (GB)	Functions	Execution Time (s)	Throughput (MB/s)	Performance
1	1	10	42	24	Moderate
2	2	20	65	31	Improved
3	5	50	110	46	High
4	8	80	150	54	Very High
5	10	100	180	58	Excellent

VII. CONCLUSION:

ArythmiAR is a novel arrhythmia diagnostic system that integrates deep learning based electrocardiogram classification with augmented reality visualisation. It provides excellent accuracy in detecting cardiac abnormalities and an interactive and intuitive platform for the medical professionals.

The system combines AI and AR technologies to enhance diagnostic accuracy and interpretability, and to facilitate better clinical decision making. The 3D view of the heart allows users to visualise the spatial relationship of the ECG signals to the heart's anatomy and makes the process of diagnosis more intuitive.

The experimental results demonstrate the effectiveness of the proposed system and its potential for real world health care applications. System enhancements in the future may include real-time monitoring, multi-lead ECG analysis and advanced deep learning models.

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