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RESEARCH ARTICLE

Enhancing Arrhythmia Diagnosis Through ECG Deep Learning Classification Deploying and Augmented Reality 3D Heart Visualization and Interaction

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ABSTRACT Cardiovascular diseases (CVDs) continue to be a leading cause of mortality globally, highlighting the urgent need for timely and accurate diagnosis. Electrocardiography (ECG) is a vital diagnostic tool for detecting and monitoring various heart conditions by analysing the heart's electrical activity; however, manually identifying ECG features and classifying heartbeats is a complex and time-consuming process that demands significant expertise. To address this challenge, we have developed ArythmiAR, a novel system that integrates Convolutional Neural Networks (CNN) with Augmented Reality (AR) to enable interactive diagnosis with 3D visualisation and real-time engagement. ArythmiAR offers several key innovations: deep learning-based ECG classification for precise arrhythmia detection, 3D heart modelling and assembly for detailed visualisation, an AR interface for deploying CNN models, 3D localisation of heart sub-regions responsible for arrhythmia anomalies, and enhanced 3D visualisation and interaction capabilities. Our study explores various ECG classification techniques, employing data rebalancing strategies to enhance model performance, with a particular focus on Multilayer Perceptron (MLP) and CNN models, which demonstrated highly competitive results on the PhysioNet MIT-BIH Arrhythmia dataset, achieving an accuracy of 99.07% with the MLP model. Remarkably, this work also involves deploying the ECG classification deep learning model within an AR environment, presenting a prototype for augmented rendering that allows users to localise, visualise, and interact with specific heart regions responsible for arrhythmias. This platform empowers medical professionals to make more accurate diagnoses and develop effective treatment strategies, thereby improving overall patient care.

INDEX TERMS Cardiac arrhythmia, classification, ECG, deep learning, augmented reality, deep learning deployment, computer-aided diagnosis, augmented rendering, 3D visualisation, interaction, 3D heart modelling, 3D localisation.

I. INTRODUCTION

Cardiovascular pathologies stand as the foremost contributors to mortality rates. The responsibility of referring a patient to a cardiologist falls upon the general practitioner. Specifically, certain individuals deemed 'at risk' necessitate continuous monitoring, particularly regarding the functionality of their cardiovascular system. Diagnosing these critical conditions represents a pivotal undertaking, conventionally executed via the non-invasive examination of the ECG signal, commonly administered at hospitals or radiology centres. Nevertheless, the manual identification of ECG signal attributes and

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heartbeat classification remains a challenging and time-intensive task [1]. Implementing automated systems capable of aiding physicians in this diagnosis process by detecting ECG signal characteristics and classifying heartbeats presents an opportunity to optimise both the time and effort expended by healthcare professionals. This, in turn, enables a more comprehensive interpretation of patient results. This issue has garnered the attention of numerous researchers, leading to the development and exploration of various methodologies. Diagnosing and preventing cardiovascular diseases can be a costly endeavour, but technology offers a promising solution through intelligent systems capable of detecting abnormalities from ECG signals. Recently, immersive technologies, such as AR, have profoundly transformed the field of medical practice [2], [3]. AR seamlessly blends the virtual and physical worlds into a real-world setting, it is a game-changing technology that offers a real-time, immersive three-dimensional (3D) experience [4]. AR has spawned a plethora of applications spanning entertainment, education, and healthcare, using the power of seamlessly fusing real and virtual aspects [3], [5], [6]. [7] delves into the healthcare sector, leveraging a marker-based AR approach that employs images as markers to enhance user-friendliness and engagement, exploring the potential of AR to revolutionise healthcare experiences.

Ballistocardiography (BCG) has emerged as a promising alternative to ECG for the diagnosis of arrhythmias, particularly for long-term and unobtrusive monitoring. While it currently lacks the precision of ECG, advancements in signal processing and machine learning are rapidly closing this gap [8]. BCG is particularly advantageous for long-term monitoring due to its non-obtrusive nature, as it can be measured using sensors embedded in mattresses, chairs, or beds [9]. ECG is the standard for arrhythmia diagnosis, providing precise electrical activity measurements of the heart. However, it requires electrodes to be attached to the body, which can be uncomfortable for long-term monitoring and may cause skin irritation [10]. BCG offers a non-contact alternative, capturing mechanical vibrations of the heart. While it is less precise than ECG in detecting specific arrhythmias, recent advancements in signal processing and machine learning have improved its accuracy. Deep learning models have been used to predict ECG signals from BCG data, achieving a mean absolute error (MAE) of 0.034 s for beat-to-beat interval accuracy [10], [11]. A study proposed a bidirectional long short-term memory (bi-LSTM) network to predict ECG signals from BCG data. This approach achieved a high correlation (0.82×0.06) between BCG and ECG-derived R-R intervals, demonstrating its potential for arrhythmia detection [8]. Another study used a stacked convolutional and recurrent neural network to improve heartbeat detection accuracy from BCG signals, outperforming traditional signal processing methods [11]. Future research may focus on improving the robustness of noise, integrating BCG with wearable technologies, and validating its clinical utility for the detection of arrhythmias [8]. Deep learning is revolutionising the medical field by enhancing diagnostic accuracy, accelerating drug discovery, and enabling personalised treatment strategies. Recent studies highlight its transformative potential, such as improving disease detection in medical imaging through advanced convolutional neural networks (CNNs) [12] and optimising therapeutic outcomes by predicting patient-specific responses to treatments. In drug development, deep learning models streamline molecular design and virtual screening, significantly reducing the time and cost of identifying viable candidates [13], [14]. In addition, frameworks that integrate multimodal data, from genomics to clinical records, are advancing precision medicine, offering customised interventions based on individual patient profiles [12]. Despite these strides, challenges like data heterogeneity, model interpretability, and ethical concerns remain critical barriers to widespread clinical adoption [15]. Collaborative efforts between AI researchers and healthcare professionals are essential to harness deep learning's full potential in transforming global healthcare.

Current advances in ECG classification for arrhythmia diagnosis have mainly focused on enhancing the accuracy of deep learning models, such as CNNs and long short-term memory (LSTMs). Nevertheless, these systems often lack intuitive interactive tools and visualisation, which are essential for medical training and clinical adoption. While AR has been investigated for surgical planning and educational purposes, its potential for real-time arrhythmia diagnosis stays under-explored. The preliminary research gap we address is the traditional ECG monitoring systems's limitations, which depend exclusively on the interpretation of static, two-dimensional waveforms. This process is prone to human error and can be subjective, as it cannot provide interactive, real-time, and spatially contextualised data visualisation for medical practitioners. Additionally, traditional methods often fail to present a comprehensive spatial understanding of the heart's electrical activity, which is critical for correct arrhythmia diagnosis and localisation. Moreover, while there are existing AR systems in the medical field, many of them concentrate especially on visualisation, such as displaying anatomical structures or delivering basic interactive features. These systems often fall short in integrating advanced diagnostic capabilities, such as real-time ECG analysis and the localisation of arrhythmia anomalies. In contrast, our proposed platform offers a comprehensive solution by combining 3D heart visualisation with ECG-based arrhythmia diagnosis. Our system not only provides 3D heart visualisation and 3D visualisation of arrhythmia anomalies but also includes an introduction to heart anatomy, arrhythmia diagnosis using deep learning, and the display of diagnosis results. Furthermore, it incorporates interactive elements such as hand-tactile interaction and voice interaction, enhancing the user experience and providing clinicians with a more intuitive and immersive diagnostic tool.

This study introduces ArythmiAR, a novel Augmented Reality based platform that uniquely integrates deep learning (DL) for ECG arrhythmia classification with immersive 3D visualisation and interactive functionalities. Our primary contributions are:

- AR-DL Integration for ECG Analysis: A novel framework that combines a high-performance DL model for real-time ECG classification (achieving state-of-the-art accuracy on the MIT-BIH dataset) with AR-driven 3D visualisation of cardiac anomalies. Unlike prior works, our system dynamically links arrhythmia predictions to interactive 3D heart models, enabling users to explore anatomical correlates of ECG abnormalities.
- Immersive AR Diagnostics and Medical Education: An AR Computer-Aided Diagnosis (CAD) system with hand-tactile and voice interaction, designed for both clinical training and practical diagnostics. This allows medical professionals to manipulate virtual heart models overlaid on real-world environments, bridging the gap between theoretical knowledge and hands-on practice.
- Balanced Data-Driven Model Optimisation: A methodological emphasis on class-balanced training data to improve arrhythmia classification robustness, addressing biases in existing ECG datasets. We demonstrate how balanced sampling enhances underrepresented-class recall without sacrificing overall accuracy.
- A user-friendly graphical interface and Validation Framework: A user-friendly graphical interface (GUI) that integrates our DL-AR pipeline, the platform is designed for scalability, supporting future extensions to other cardiac conditions.

Figure 1 illustrates the overarching flowchart depicting the contributions made within our paper. The ultimate goal is to achieve optimal performance while saving time and reducing human effort. To attain this objective, we employ a variety of machine learning models that have demonstrated effectiveness in previous studies related to ECG signal classification, including CNN, and MLP. In this study, we leverage the MIT-BIH dataset [16], a valuable resource available to the ECG signal processing community, to create a more balanced dataset and achieve superior classification performance.

The article is structured as follows: in Section II, we delve into the field of arrhythmia classification, explaining the machine learning techniques used, with a particular emphasis on deep learning-based approaches. This section also explores the use of AR technology in healthcare and its potential to revolutionise cardiovascular disease diagnosis and medical practice. In Section III, we outline our proposed contributions, including ECG classification based on deep learning development. This section also presents the experimental results and comparative analyses. Section IV introduces a mobile AR platform, ArythmiAR, designed to visualise and interact with arrhythmia classification results. In this section, We explore the AR environment, 3D modelling and assembly of the human heart, as well as the 3D visualisation of ECG classification results, with a focus on localising the heart sub-regions responsible for arrhythmia anomalies. We also examine AR interactions enabled through voice commands and hand-tactile gestures, comparing our approach to recent advancements in AR overlay rendering. Finally, Section V concludes the article, highlighting our achievements and discussing future research directions.

II. RELATED WORK

In this section, we will delve into recent advancements in ECG abnormality classification using machine learning methods, focusing on deep learning-based approaches for ECG classification. Alfaras et al. [17] have introduced a highly efficient and fully automated ECG arrhythmia classifier. This classifier relies on a straightforward brain-inspired machine-learning technique called echo state networks. It employs a neural network structure with a sparsely connected hidden layer and minimalistic feature processing, utilising just a single ECG lead. The learning and validation procedures adhere to an inter-patient approach. The performance of this heartbeat classifier has been rigorously assessed on two ECG databases: MIT-BIH AR and AHA [16]. In their study, Mohamed Suhail and colleagues [18] introduced a comprehensive framework for automatic heart disease detection. Their approach combines multi-field feature extraction and non-linear analysis of electrocardiogram (ECG) data. The primary goal of this research is to establish a model for future cardiovascular disease diagnosis by leveraging ECG analysis and symptom-based detection. The study utilises discrete wavelet transform methods for pre-processing to effectively eliminate unwanted noise and artefacts. Additionally, a decomposed vector nonlinear neural network is employed to evaluate the model's performance, yielding impressive results: sensitivity, specificity, and accuracy metrics of 92.0%, 89.33%, and 90.67%, respectively. [19] introduced an artificial intelligence-based technique for the detection of atrial fibrillation. Their approach commenced with pre-processing the electrocardiogram (ECG) data through a two-stage median filter and a least-squares smoothing filter. To enhance the efficiency of their system, a two-step normalisation process was employed. Initially, they applied max-min normalisation before segmentation, followed by z-score normalisation. The conversion of the 1-D ECG signal into a time-frequency representation was achieved using a spectrogram. Subsequently, the performance of their technique was evaluated using a Bi-LSTM model on both the 1-D ECG data and the time-frequency ECG data. Atul Anand et al. [20] developed an intelligent ST-CNN-GAP-5 explainable decision model for analysing ECG data related to cardiac disorders. They applied multiple deep neural networks to a publicly available PTB-XL ECG signal dataset to detect cardiac disorders. The results achieved an accuracy of 95.8% and an AUC of 99.46%. These metrics are highly competitive with the current leading models in the field. Notably, the model's capacity to discern relevant

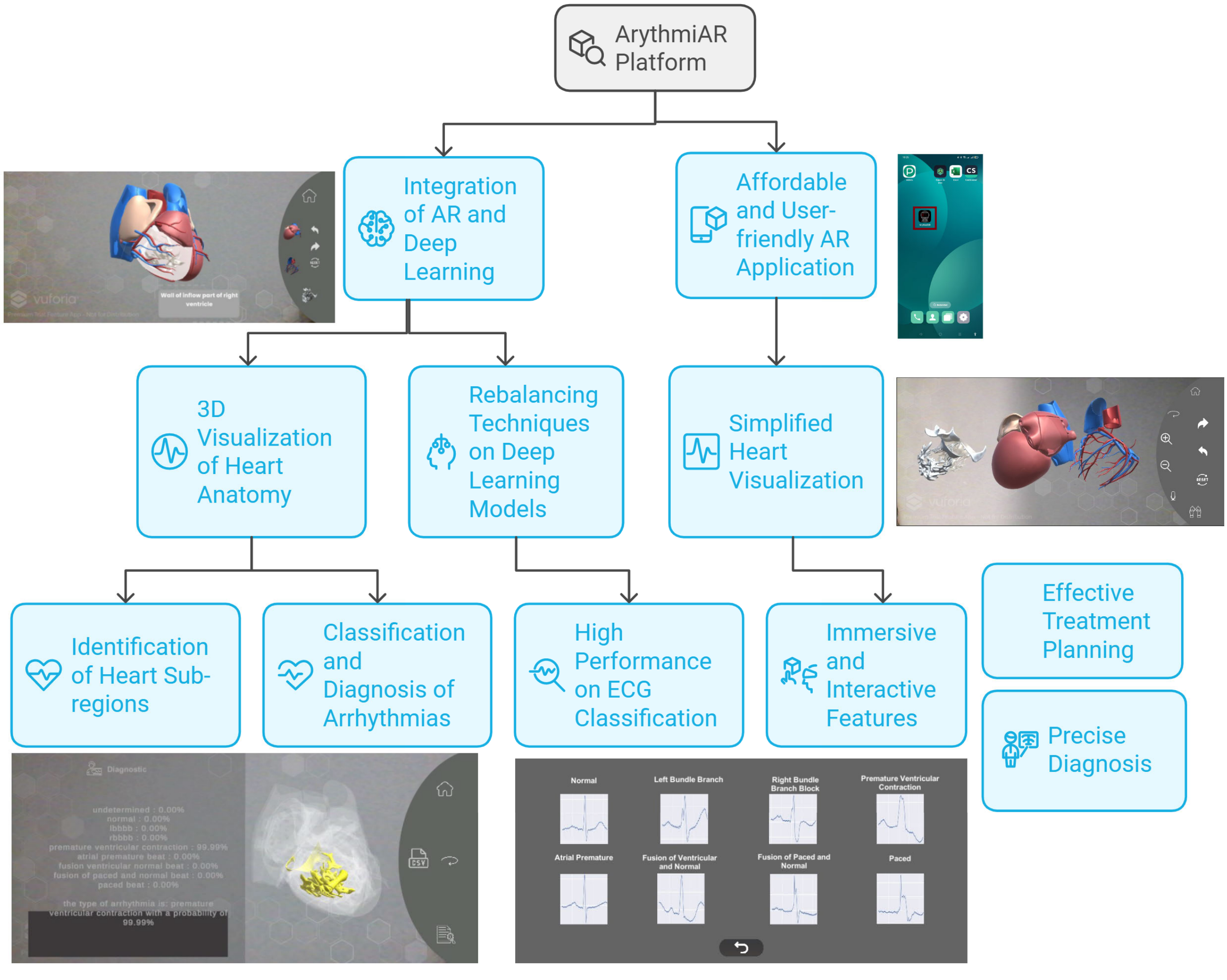


FIGURE 1. **Workflow chart for cardiac arrhythmia diagnosis based deep learning deployment using augmented reality visualisation and interaction.**

changes in ECG waveforms, a critical requirement for clinicians, renders it highly explainable and suitable for diagnostic purposes. The deployment of such models has the potential to alleviate the strain on medical infrastructure, particularly in densely populated low- and middle-income countries. Hu et al. [21], introduced an innovative approach to enhance arrhythmia classification performance. They presented a novel deep-learning neural network based on an ECG DETR transformer, capable of detecting arrhythmias within continuous segments of single-lead ECGs. Unlike beat-by-beat classification methods, this model predicts the positions and categories of all heartbeats within an ECG, eliminating the need for explicit heartbeat segmentation. Consequently, their proposed method represents an end-to-end arrhythmia detection algorithm. To validate the performance and generalisation of their approach, experiments were conducted using the MIT-BIH arrhythmia database and the MIT-BIH atrial fibrillation database. These experiments encompassed three distinct arrhythmia detection tasks, each with 8, 4, and 2 labels, respectively, and employed a 10-fold cross-validation methodology. The results indicate that the proposed method yields performance comparable to prior works, considering both heartbeat segmentation and classification. Specifically, it achieved an overall accuracy of 99.12%, 99.49%, and 99.23% for the three aforementioned tasks. When converting ECG data into a 2D image representation, [22] assumed that the Convolutional Neural Network (CNN) model would effectively filter out noise parameters during the feature extraction process in both the pooling and convolution layers. To enhance the model's capabilities in dataset recognition, the final layer of the CNN was fine-tuned using Google's Inception V3 model. This study aimed to develop and implement a diagnostic support system capable of collecting, interpreting, and analysing clinical data and ECG biosignals from patients, particularly in remote regions lacking access to ECG facilities. To achieve this, binary and quinary classifications were created for training and evaluating the ECG datasets. The achieved accuracy rates were impressive, with a 98.73% accuracy for binary classification and a 97.33% accuracy for quinary classification.

Deep learning models, exemplified by Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), exhibit remarkable performance in ECG classification tasks, consistently achieving high accuracy. These models automate the analysis process by extracting meaningful features from raw ECG signals while mitigating the potential for human error. Their inherent scalability renders them highly suitable for integration into extensive healthcare systems or for the continuous processing of monitoring data. Consequently, they alleviate the reliance on manual interpretation and subjective feature engineering, enhancing their applicability in clinical and diagnostic contexts. However, it is essential to acknowledge that deep learning-based ECG classification methods also present several challenges. This includes substantial data requirements, issues related to data imbalance, susceptibility to overfitting, high computational resource demands, model complexity, concerns regarding data privacy, and difficulties in generalising across diverse datasets or populations. These challenges can result in biased predictions, suboptimal generalisation performance, and increased costs for healthcare institutions and researchers. Moreover, the intricacy of deep neural networks and the necessity for meticulous data handling practices can introduce additional complexities. The authors have proposed a novel deep learning model named EMD-LSTM-CNN (ELC), which integrates Empirical Mode Decomposition (EMD), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) [23]. The ELC model uses EMD to extract the trend term from HR and RR signals, while CNN and LSTM are applied for feature extraction and processing, respectively. The experimental results demonstrated that the ELC model significantly outperformed traditional FFT and WT algorithms, particularly in handling non-stationary vibration signals. This superior performance suggests that the ELC model is well-suited for physiological monitoring and holds promise for future clinical applications.

CLINet [24], which integrates convolution, involution, and LSTM layers, excels in capturing intricate temporal dependencies and achieves high accuracy in arrhythmia detection. However, its reliance on LSTM components introduces significant computational complexity, limiting its applicability in real-time or resource-constrained environments. The hybrid ResNet-Random Forest approach [25] leverages the strengths of both deep learning and ensemble methods, resulting in robust performance and high accuracy across diverse datasets. Yet, this method suffers from increased computational overhead and potential scalability issues due to the complexity of managing multiple models. The MobileViT-based approach [26] emphasises computational efficiency and is highly suitable for mobile and edge devices, offering a lightweight solution for ECG classification. Nevertheless, it may compromise accuracy and struggle with handling class imbalances due to its simplified architecture. In contrast, our proposed models (MLP and CNN) strike a balance between accuracy, precision, and computational efficiency. By integrating advanced balancing techniques, our models effectively mitigate class imbalance issues, enhancing robustness and reliability, particularly in scenarios with under-represented arrhythmia classes. Our models outperform CLINet in terms of precision and F1-score, surpass the hybrid ResNet-Random Forest approach in computational efficiency, and maintain competitive accuracy with the MobileViT-based approach while offering superior performance in handling class imbalances. While our models require fine-tuning and may demand more computational resources during the training phase, its streamlined architecture ensures efficient performance without compromising on accuracy. These comparisons underscore the advancements of our methodology, demonstrating its potential as a robust and efficient solution for arrhythmia detection in practical applications. In this study, we address the challenge of imbalanced data by employing both undersampling and oversampling techniques in conjunction with two deep learning models: MLP and CNN.

ECG visualisation plays a key role in aiding clinicians in cardiac activity interpretation, allowing them to detect irregularities such as conduction abnormalities, arrhythmias, and ischemic events [18], [27], [28]. The ECG data visualisation involves the display of the heart's electrical signals on a graph, typically in the form of a series of waves and complexes. By analysing and observing these patterns, medical practitioners can assess the heart's rhythm, identify abnormalities, and diagnose various cardiac conditions. In an augmented reality aid diagnosis system, clinicians can observe and analyse ECG signals in a three-dimensional space, allowing for a deeper comprehension of cardiac dynamics [29]. The visual representation in AR enables healthcare professionals to navigate through intricate details, identify anomalies, and gain insights into the temporal aspects of cardiac events. In the healthcare sector, the utilisation of AR is experiencing significant growth across various domains, including surgical procedures, medical diagnostics, and patient recovery processes. This surge in AR adoption reflects a burgeoning demand for innovative solutions that have the potential to enhance and advance current medical practices [30]. Consequently, this trend presents a compelling opportunity for designers, computer programmers, engineers, and end-users to explore the vast potential of AR technology in shaping the development of valuable applications infused with computer-generated elements. The intersection of healthcare and AR not only promises to revolutionise the way medical professionals operate but also holds the potential to improve patient outcomes and the overall quality of healthcare delivery [31]. As Android smartphones are widely accessible, the AR application developed by [7] opted for an Android smartphone equipped with ARCore support as its platform of choice [32].

To engage with the application, users simply need to scan a predefined marker using their Android smartphone. Upon scanning, a detailed 3D model of the human heart materialises on the device's screen in real-time. Subsequently, users can explore a captivating educational experience by navigating through various heart regions and accessing comprehensive information simply by interacting with buttons on their smartphone screens. [33] delineates the development of a web application leveraging augmented reality to enhance users' comprehension of the human heart's anatomy. The system assists users in comprehending the anatomy of the human heart. However, it is not suitable for users who do not have an internet connection. In [34], the authors used an AR application for smartphones and tablets to investigate the efficacy of a learning sequence of activities connected to the cardiac cycle. The authors were concerned about students' capacity to draw and name pictures resembling heart functions after experiencing the learning sequence via AR. Their system offers an effective scenario for learning physiology content. It enables users to zoom in, zoom out, and rotate the 360° cardiac model along any axis. However, it does have limitations when it comes to interactivity with the model in certain aspects. The authors in [35] demonstrated the efficacy of employing AR in the teaching of heart anatomy. They implemented a heart learning system specifically designed for Thai students, which incorporated bilingual content in both Thai and English. However, it's worth noting that their system primarily offered augmented visualisation without interactive features, which somewhat constrained its utility as an educational tool. In their work [36], the authors proposed a mobile application for learning human anatomy using augmented reality. The system provides detailed explanations about virtual objects, allowing users to interact with them. However, a limitation of this work is that the virtual objects are not animated.

In the context of this research, one of the primary objectives is to advance current ECG arrhythmia classification methods by incorporating augmented reality visualisation and immersive 3D interaction capabilities. This approach aims to provide users with a more realistic diagnostic and training tool. The proposed AR-enhanced ECG classification model has diverse real-world applications, including clinical decision support in hospitals for real-time arrhythmia detection (e.g., atrial fibrillation, ventricular tachycardia) during critical care, wearable health tech integration (e.g., smartwatches) to enable continuous cardiac monitoring and early alerts for at-risk individuals, and emergency medicine applications where paramedics using AR headsets could prioritise life-threatening conditions like STEMI during pre-hospital triage. It could also enhance telemedicine by automating ECG analysis in underserved regions, serve as an interactive training tool for medical education, support personalised preventive healthcare through long-term ECG trend analysis for chronic disease patients, and improve drug safety monitoring by detecting medication-induced cardiac abnormalities. These applications collectively aim to reduce diagnostic delays, improve accessibility, and enhance clinical outcomes through real-time, AR-augmented insights.

TABLE 1. Arrythmia MIT-BIH dataset description.

Number of samples	109446
Number of classes	08
Class	**Beat Description**
1	Normal
2	Left Bundle Branch Block Beat
3	Right Bundle Branch Block Beat
4	Premature Ventricular Contraction
5	Atrial Premature Beat
6	Fusion of Ventricular and Normal
7	Fusion of Paced and Normal
8	Paced
Sampling frequency	360 Hz

III. ECG CLASSIFICATION FOR ARRHYTHMIA DIAGNOSIS

A. DATASET

We used MIT-BIH Arrhythmia Database [16], which contains 48 half-hour segments of two-channel ambulatory ECG recordings from 47 subjects involved in research by the BIH Arrhythmia Laboratory between 1975 and 1979. Among 4000 24-hour ambulatory ECG recordings, 23 were randomly chosen for this database. The recordings were digitised at 360 samples per second per channel with an 11-bit resolution over a 10 mV range. Cardiologists independently annotated each record, resolving disagreements to create a computer-readable reference dataset of 109446 annotations included with the database. Table 1 gives a short description of the used dataset.

1) DATA IMBALANCE

In real-world classification tasks, class imbalance poses a significant challenge, where underrepresented classes—often critical to the problem—are overshadowed by majority classes. This imbalance biases standard learning algorithms toward the majority class, degrading predictive performance for underrepresented-class recognition. To address this, robust systems must be designed to mitigate such bias and adapt to skewed data distributions. This section explores strategies for handling imbalanced datasets in classification.

A common approach involves resampling the training set to balance class distributions, enabling standard algorithms to learn effectively. These resampling techniques fall into two categories:

1) Data-level approaches: Modifying the dataset itself (e.g., oversampling the underrepresented class or undersampling the majority class).
2) Algorithm-level approaches: Adjusting the learning process to prioritise underrepresented-class instances (e.g., cost-sensitive learning).

Oversampling is a technique used to balance datasets by generating synthetic examples from the underrepresented class. Among the various methods, the Synthetic Minority Oversampling Technique (SMOTE) is the most widely used, as it creates new synthetic samples rather than duplicating existing ones, helping improve model generalisation. From the confusion matrix, we observe that classifiers trained on synthetic examples generalise well, identify the underrepresented class (true negatives), and produce fewer false positives compared to undersampling. The key advantages of SMOTE include reducing overfitting caused by random oversampling and preserving all original data, preventing information loss. However, a notable drawback is that SMOTE does not consider neighbouring examples, which may belong to other classes, potentially increasing class overlap and introducing noise. Furthermore, it is less effective for high-dimensional data, where feature sparsity can affect the quality of the synthetic samples generated. We expanded our dataset to encompass 400,000 samples by implementing oversampling techniques. However, it's crucial to highlight that SMOTE doesn't account for neighbouring instances that may belong to other classes when creating synthetic examples. This oversight can increase class overlap and introduce additional noise, rendering SMOTE less suitable for datasets with high-dimensional features.

Undersampling is a technique used to balance datasets by reducing the number of samples from the majority class to match those of the underrepresented class. This can be achieved using various methods, such as random sampling, where a subset of the majority class is randomly selected, or NearMiss, which applies heuristic rules to select representative samples. While undersampling is generally less effective than oversampling in identifying the majority class (true positives), it performs better at recognising the underrepresented class and results in fewer false negatives. One major advantage of undersampling is that it helps mitigate bias in machine learning models by preventing them from being overly influenced by the majority class, reducing the risk of the accuracy paradox, where a model appears highly accurate but largely predicts the majority class. Additionally, undersampling reduces storage requirements and improves computational efficiency. However, its main drawback is the potential loss of valuable information when removing majority class examples, which may result in a biased dataset that does not accurately reflect real-world distributions, leading to poor classifier performance on unseen data. Table 7 displays the comparative results obtained from various datasets following the implementation of both under and over-sampling techniques. Figure 2 showcases the effect of resampling techniques on the training and testing sets. However, it is crucial to exercise caution when removing a substantial number of majority class examples to achieve class balance. This process may result in significant data loss. Moreover, the samples chosen from the majority class might be biased, potentially failing to accurately represent the real-world scenario. Consequently, the analysis's outcomes may be inaccurate, and classifier performance may falter when applied to unseen, real-world data. Through the application of subsampling techniques, we acquired a dataset comprising 3205 samples.

To summarise, each signal consists of 187 samples, which refers to the length of each individual heartbeat signal in the dataset. The total number of samples in the original dataset is 109,446, representing the cumulative count of all heartbeat signals before any resampling techniques were applied. To address class imbalance, we applied undersampling techniques, resulting in a reduced dataset comprising 3,205 samples by selectively reducing samples from overrepresented classes. Additionally, we applied oversampling techniques, generating an expanded dataset of 400,000 samples by artificially increasing samples from underrepresented classes to achieve better class balance.

B. USED DEEP LEARNING APPROACHES FOR ECG CLASSIFICATION

We employed two established deep learning models, namely CNN and MLP, for the classification of ECG data. Recurrent neural network architectures can take many different forms, one of which is a standard MLP with loops added [37]. These networks leverage the nonlinear mapping capabilities of the MLP while incorporating memory. Other recurrent architectures have more uniform structures, where neurons may be interconnected in complex ways and use stochastic activation functions to introduce randomness into the learning process.

- A Convolutional Neural Network (CNN) is a deep learning architecture designed to process grid-structured data such as images, videos, and spectrograms by leveraging spatial hierarchies through convolutional operations [38]. CNNs excel at capturing local patterns (e.g., edges, textures) and progressively abstracting them into higher-level features (e.g., shapes, objects). A typical CNN consists of several layers: convolutional layers, which extract spatial features using learnable filters (e.g., 32, 64 kernels of size 3×3 or 5×5), pooling layers (max or average pooling) that downsample feature maps to reduce computational complexity and mitigate overfitting, and activation layers (e.g., ReLU) that introduce non-linearity. The fully connected (dense) layer at the end is responsible for classification based on extracted features. Additional layers such as dropout (which deactivates neurons randomly during training) and batch normalisation (which normalises layer inputs) improve generalisation and stability. CNN architectures use different activation functions: ReLU is common for convolutional and fully connected layers, Softmax is applied for multi-class classification, and Sigmoid/Linear is used for binary classification or regression. Key hyperparameters include the number of filters (increasing with depth, e.g., $32 \rightarrow 64 \rightarrow 128$), kernel size (e.g., 3×3 for fine details, 7×7 for broader patterns), pooling strategies, and network depth (e.g., ResNet-50 for complex tasks) [38]. The training process involves optimising learning rates

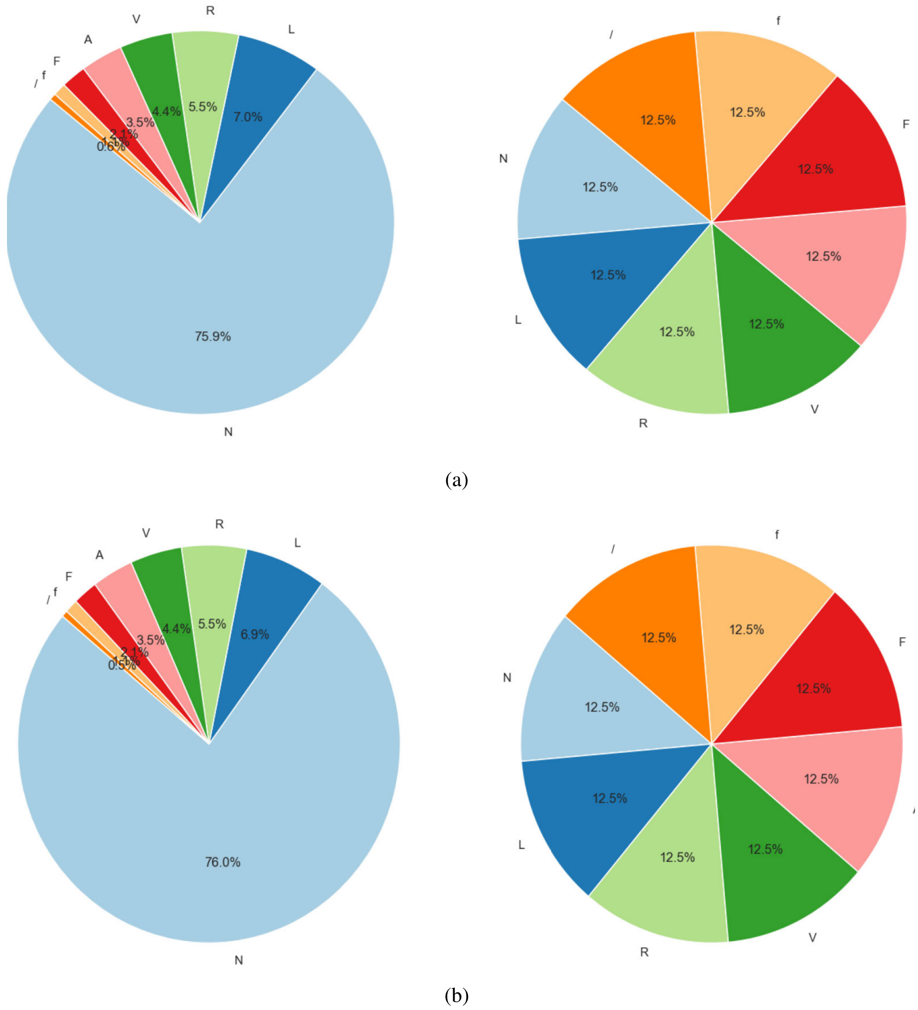


FIGURE 2. **Class distributions before and after resampling. (a) Training set, (b) Test set.**

(0.001-0.0001), batch sizes (32-256), and optimisers (Adam, SGD with momentum), while regularisation techniques such as dropout (0.2-0.5), L2 weight decay, and data augmentation (rotation, flipping, scaling) enhance model robustness.

- A Multi-Layer Perceptron (MLP) is a feedforward neural network that consists of at least one hidden layer between the input and output layers [37]. It is designed to process static (non-sequential) data by passing information in a unidirectional manner (input → hidden → output). The input layer contains neurons equal to the number of features in the dataset (e.g., 784 for MNIST images). The hidden layers, typically ranging from one to three fully connected layers, contain 32 to 1024 neurons per layer, depending on the complexity of the data. The output layer has neurons corresponding to the number of target classes (e.g., 10 for digit classification) or a single neuron for regression tasks. Activation functions such as ReLU, Sigmoid, and Tanh are used in hidden layers to introduce non-linearity, while Softmax is commonly used in classification tasks to convert logits into probabilities, and Linear/Sigmoid is applied for regression. The network's performance is influenced by several key hyperparameters, including architecture depth (number of hidden layers), width (neurons per layer), and optimisation strategies such as learning rate (e.g., 0.001) and choice of optimiser (Adam, SGD). To prevent overfitting, regularisation techniques like dropout (0.2-0.5) and L1/L2 weight penalties are applied. The training process involves tuning batch size (32-512) and epochs, with early stopping mechanisms to optimise generalisation.

Tables 2 and 3 provide a detailed breakdown of the architectures for the CNN and MLP models, respectively. Table 2 presents the kernel details for each layer and the total number of parameters in the CNN model, while Table 3 outlines the layer configurations and parameter counts for the MLP model.

We established functions to construct our models with specific parameters. The chosen cost function referred to as "Loss" is "categorical_crossentropy" employed by the model to minimise errors. For optimisation, we opt for

TABLE 2. Convolutional neural network (CNN).

Layer (type)	Output Shape	Param #
conv1d_1 (Conv1D) (Kernel size: 5)	(None, 183, 32)	192
batch_normalization_1	(None, 183, 32)	128
max_pooling1d_1 (MaxPooling1D)	(None, 91, 32)	0
conv1d_2 (Conv1D) (Kernel size: 5)	(None, 87, 64)	10,304
batch_normalization_2	(None, 87, 64)	256
max_pooling1d_2 (MaxPooling1D)	(None, 43, 64)	0
conv1d_3 (Conv1D) (Kernel size: 3)	(None, 41, 128)	24,704
batch_normalization_3	(None, 41, 128)	512
max_pooling1d_3 (MaxPooling1D)	(None, 20, 128)	0
flatten_1 (Flatten)	(None, 2560)	0
dense_5 (Dense)	(None, 128)	327,808
dropout_3 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 8)	1,032

TABLE 3. Multi-layer perceptron (MLP).

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 256)	48,128
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32,896
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 64)	8,256
dense_4 (Dense)	(None, 8)	520

the highly effective stochastic gradient descent algorithm ''Adam'' due to its self-adjusting nature and proven success across diverse problem sets. In evaluating model performance for a classification problem, we utilise the metric ''accuracy'', providing a measure of accuracy as a key indicator. Before initiating the training process for our predictive model, an exploration was undertaken to determine optimal hyperparameters through Gridsearch methodologies. The outcome of this exploration informed the selection of specific parameters, the optimal batch size was identified as 32 through GridSearch and the number of epochs was set to 10, defining the complete passes made through the training dataset in our setup. We used the raw ECG signals found in the data set for each ECG sample. Each signal consisted of 187 samples, reflecting the original voltage measurements obtained during ECG recording. We used these raw signals directly as input to our model without any pre-processing or feature extraction steps. For training the CNN and MLP models, we utilised Google Colab [39], a cloud-based platform that provides access to GPUs and TPUs, enabling efficient model training and execution. Additionally, we employed a high-performance workstation equipped with two Intel Xeon® Silver 4114 processors (20 cores @ 2.199 GHz), 256 GB RAM, an NVIDIA Quadro P2000 GPU, and 2 TB HDD storage to enhance computational efficiency further.

Tables 6 and 7 present a summary of key performance metrics for the CNN and MLP models. Table 4 includes the number of parameters, floating-point operations (FLOPs), and inference time, providing a comparative analysis of computational efficiency and complexity for both architectures. While MLP offers a simpler architecture, CNN is better suited for ECG signal analysis due to their

TABLE 4. Summary of metrics for CNN and MLP models.

Metric	CNN	MLP
Number of parameters	364,040	89,800
Number of floating operations	4.51 MFLOPS	178.7 kFLOPS
Inference time	1 ms/sample	0.05 ms/sample

TABLE 5. Dataset splits.

Split	Number of Samples	Percentage	Notes
Training Set	320,000	80%	Used to train the model.
Validation Set	40,000	10%	Used for hyperparameter tuning.
Test Set	40,000	10%	Final evaluation on unseen data.

ability to extract temporal and spatial features, making it suitable for real-time diagnostics in next-generation AR healthcare applications. ECG signals are time-series data with subtle, localised abnormalities (e.g., irregular R-peaks, ST-segment deviations), which CNNs effectively capture using convolutional filters. Although deploying CNNs in AR environments for arrhythmia diagnosis presents challenges, our research demonstrates its feasibility and effectiveness.

To ensure reliable model evaluation, the data was partitioned into three subsets following standard machine learning practices. This split mitigates overfitting while maintaining sufficient samples for training and validation. Table 5 summarises the distribution of samples across the splits, preserving an 80-10-10 ratio to balance model generalisation and evaluation rigour.

C. USED METRICS

For our evaluation of the ECG classification system, we used the following metrics: Mean Squared Error (MSE) (equation 1), Accuracy (ACC) (equation 2), Sensitivity (equation 3, Specificity (equation 4), MCC (Matthews Correlation Coefficient) (equation 5), Kappa (equation 6), and F1-score (equation 7) with parameter definitions:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

where:

$$n = \text{Number of data points}$$
$$y_i = \text{Actual value for the } i\text{-th data point}$$
$$\hat{y}_i = \text{Predicted value for the } i\text{-th data point}$$

$$\text{ACC} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (5)$$

$$Kappa = \frac{P_o - P_e}{1 - P_e} \quad (6)$$

where:

$$P_o = \frac{TP + TN}{TP + TN + FP + FN}$$

$$P_e = \frac{(TP + FP)(TP + FN) + (TN + FN)(TN + FP)}{(TP + TN + FP + FN)^2}$$

$$F1 - score = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (7)$$

where:

$$TP = \text{True Positives}$$
$$TN = \text{True Negatives}$$
$$FP = \text{False Positives}$$
$$FN = \text{False Negatives}$$

Although the original ECG dataset was unbalanced, data pre-processing techniques were applied to balance the class distribution. These metrics were selected to collectively represent the model's ability to correctly classify different arrhythmia types while mitigating the influence of imbalanced class distributions. By incorporating these metrics, we aim to offer a comprehensive evaluation that goes beyond basic accuracy, ensuring a more robust and meaningful assessment of the performance of our proposed methodology. Figure 3 presents the confusion matrices for the MLP and CNN models, highlighting their classification performance across all eight arrhythmia classes. The training loss and validation loss curves for the MLP and CNN models are presented in Figures 4 and 5.

D. ECG CLASSIFICATION RESULTS AND COMPARISON

The performance metrics presented in the table highlight the effectiveness of our proposed models, MLP and CNN, on the MIT-BIH dataset. The MLP model achieved an accuracy of 99.07%, while the CNN model attained 98.58%, demonstrating high classification performance. The sensitivity and specificity values for both models indicate their ability to correctly identify both positive and negative instances, with the MLP model showing slightly superior performance (99.07% sensitivity and 99.84% specificity) compared to CNN (98.585% sensitivity and 99.677% specificity). The Matthews Correlation Coefficient (MCC) and Cohen's Kappa further validate the robustness of our models. The MLP model recorded an MCC of 0.9894 and a Kappa score of 0.9893, signifying strong agreement between predicted and actual labels. Similarly, the CNN model achieved an MCC of 0.984 and a Kappa score of 0.984, demonstrating reliable classification performance despite being slightly lower than MLP. The F1-score, which balances precision and recall, confirms the high classification ability of both models. The MLP model obtained an F1-score of 99.07%, while CNN achieved 98.60%, reinforcing the effectiveness of our approach. The slightly higher performance of MLP may be attributed to its ability to capture complex non-linear patterns in the data without losing spatial information, while CNN relies more on spatial feature extraction, which may be less effective for certain variations of the ECG signal. The results depicted into table 6 suggest that both models provide excellent classification performance, with MLP slightly outperforming CNN in most metrics. However, CNN remains a competitive approach, particularly when handling structured spatial features in medical signal analysis. Future improvements could explore enhanced architectures that integrate complementary inductive biases, such as attention mechanisms or graph-based operations, to further improve classification accuracy and generalisation.

Table 8 provides an insightful comparison between various methodologies applied to diverse datasets for ECG classification. In particular, we would like to draw attention to our method's performance on the MIT-BIH dataset.

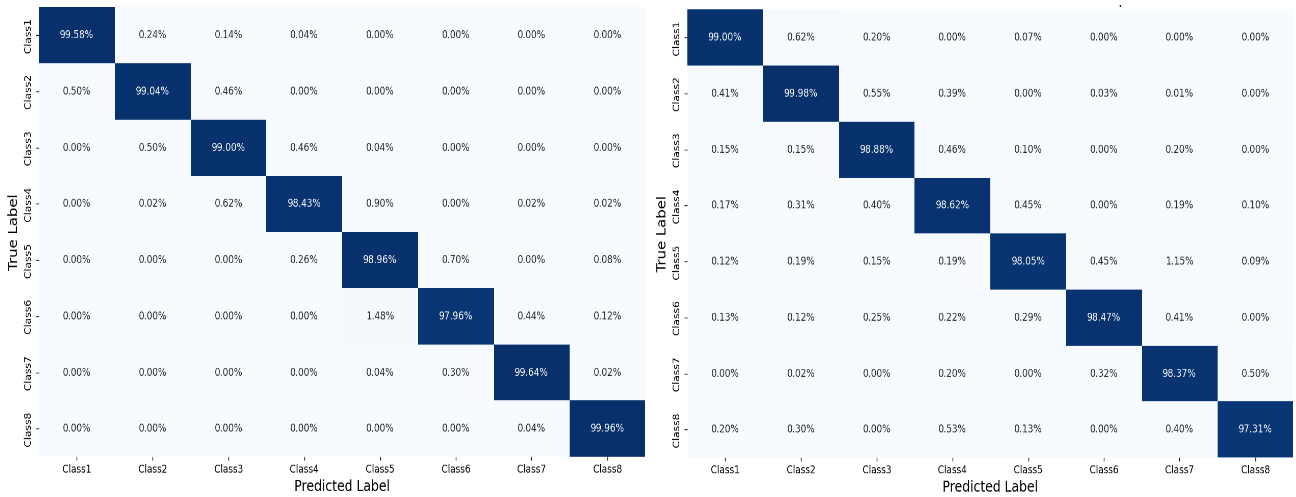
Compared to the referenced works, our proposed approach, employing MLP and CNN architectures, showcases compelling performance metrics. Specifically, our method achieves an accuracy of 99.07%, surpassing the reported accuracies in the comparative works. Additionally, it demonstrates robustness with an accuracy of 98.58% on a secondary metric, further affirming its consistency and reliability in classification tasks.

It is critical to note that our methodology's superior performance contributes significantly to the field by achieving heightened accuracy without compromising other essential metrics. These outcomes underscore the efficacy and potential applicability of our proposed architecture in ECG signal classification tasks, especially concerning the MIT-BIH dataset.

Table 8 provides a comprehensive comparative analysis of our proposed methodology against state-of-the-art machine learning and deep learning approaches for ECG arrhythmia classification. This section will delve into the nuanced performance measures, elucidating how our approach stands in contrast to existing solutions.

Table 8 showcases a diverse array of methodologies applied across various datasets, encompassing MIT-BIH, MIT-BIH AR, AHA, UCI, PhysioNet, and others. This diversity reflects the intricate real-world complexity inherent in ECG arrhythmia classification, underscoring the necessity to consider multiple data sources and arrhythmia types.

The recent advancements in ECG signal classification for arrhythmia detection have demonstrated significant progress through innovative deep learning architectures. [24] introduced CLINet, a novel framework combining convolution, involution, and LSTM layers, achieving state-of-the-art performance with an accuracy of 99.26%. This approach effectively captures both spatial and temporal features of ECG signals, making it highly robust for arrhythmia classification. In contrast, [25] proposed a hybrid machine learning and deep learning approach, integrating residual neural



(a) (b)

FIGURE 3. Confusion matrix: (a) MLP model, (b) CNN model.

TABLE 6. Proposed models performance (MLP and CNN) on the MIT-BIH dataset.

Dataset	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	MCC	Kappa	F1-score (%)
MIT-BIH	MLP	99.07	99.07	99.84	0.9894	0.9893	99.07
	CNN	98.58	98.585	99.677	0.984	0.984	98.60

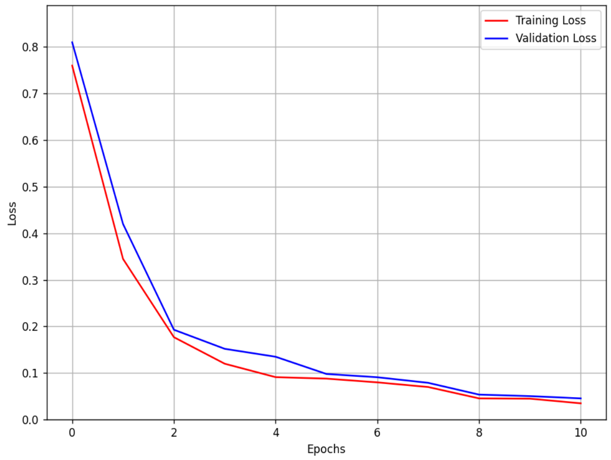


FIGURE 4. Training and validation MLP loss curves.

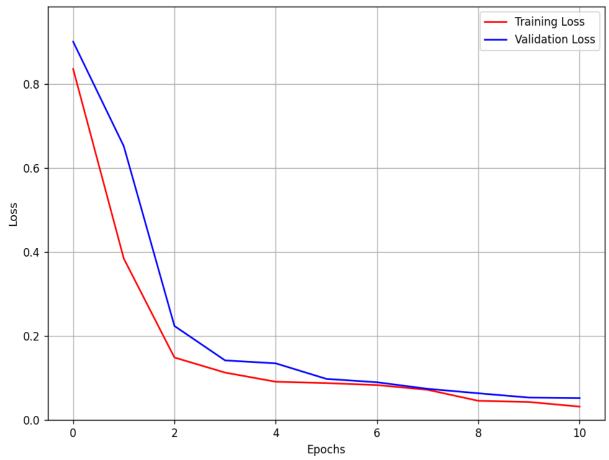


FIGURE 5. Training and validation CNN loss curves.

TABLE 7. Comparative outcomes across diverse datasets after the implementation of rebalancing methodologies.

Dataset used	method	ACC	MSE	MCC
Intial dataset	RNN	83.15 %	0.524	8.03%
	LSTM	86.23 %	0.4804	9.23%
	MLP	97.89 %	0.11	92.28%
	CNN	98.56%	0.0556	84.20%
Under sampling	MLP	89.09%	0.3212	85.62%
	CNN	98.52%	0.0653	94.12%
Over sampling	MLP	99.07 %	0.0456	98.94%
	CNN	98.58 %	0.0524	98.4%

networks (ResNet) with random forest classifiers, achieving an accuracy of 98.97%. While slightly lower in performance compared to CLINet, this method emphasises interpretability and computational efficiency, leveraging the strengths of both traditional machine learning and deep learning. Meanwhile, [26] explored a MobileViT-based approach using ECG scalograms, focusing on lightweight and mobile-friendly deployment. Although its accuracy is not explicitly stated, the use of vision transformers (ViT) and scalograms highlights a promising direction for resource-constrained environments. Regarding performance, our methodology, which leverages MLP and CNN, demonstrates exceptional prowess. Notably, our approach achieves impressive accuracy levels of 99.07%

TABLE 8. Comparing our proposal with the state-of-the-art machine learning and deep learning methods.

Work	Dataset	Approach	Performance
[40]	MIT-BIH	GDB Tree [41], Binary and Multiclass Random Forest Classification [42]	Pre.= 96,75 % ,97,98 % , 98,03%
[17]	MIT-BIH AR and AHA	ECN (Echo State Network) [17]	ACC. = 98.6%
[19]	MIT-BIH NSRD	Bi-LSTM [43]	Pre.= 98,85%
[44]	MIT-BIH	MLP [37]	ACC.=98.72%
[21]	MIT-BIH arrhythmia , MIT-BIH Atrial fibrillation	D-CNN [21]	Pre. = 99,12 %
[22]	MIT-BIH, PTB-XL, bradycardia, Fantasia, PAF Prediction Challenge Databases	CNN [38]	ACC. = 98.73%, F1-scores = 96.83% for binary classification / ACC. = 97.33%, F1 score = 99.21% for 4 classes.
[45]	MIT-BIH	UNet+ BLSTM [45]	ACC.=98.3%
[25]	MIT-BIH	LSTM [46]	ACC.=99.26%
[26]	MIT-BIH	MobileViT [26]	ACC.=98.97%
Ours	**MIT-BIH**	**MLP** **CNN**	**ACC.=99.07%** **ACC.= 98.58%**

and 98.58% for these two methodologies, Establishing the reliability and robustness of our approach in delivering ECG arrhythmia assessments with high classification performance. This marks a substantial advancement compared to prior approaches documented in [17], [18], [19], [40], [47], and [44], where reported accuracy figures ranged from 80.8% to 98.72%. Moreover, our method's precision metrics are notably competitive. In contrast to reference [40], which employs Gradient Boosting Decision Trees (GDB Tree) and Random Forest Classification, our approach showcases comparable or even superior precision rates, particularly in addressing the challenging multiclass classification task. The competitive performance of our methodology can be attributed to the balancing techniques applied to the dataset, which mitigate class imbalance issues and enhance the model's ability to generalise across underrepresented classes. This ensures that our approach not only achieves high accuracy but also maintains robust precision and recall metrics, making it a reliable solution for real-world ECG arrhythmia diagnosis.

Furthermore, the outperformance of our methodology over [18], which transformed data into discrete wavelets and employed Recurrent Neural Networks (RNN) achieving an accuracy of 90.67%, underscores the significance of our combined MLP and CNN architecture in attaining superior accuracy.

Noteworthy is our methodology's exceptional performance specifically on the MIT-BIH dataset, a widely recognised benchmark dataset in ECG arrhythmia classification. The achieved high accuracy and precision levels on this dataset distinctly showcase the practical suitability of our method for applications in healthcare and medical diagnostics.

IV. ArythmiAR: AN AUGMENTED REALITY PLATFORM FEATURING CNN-BASED DEPLOYMENT FOR ARRHYTHMIA DIAGNOSIS

AR ECG categorisation can enhance patient care, medical diagnosis, and training. In this section, we will outline one of our major contributions: the deep learning deployment using Unity3D [48] and Flask [49], the Mobile AR platform, and the 3D visualisation and interaction concept. This includes AR rendering, 3D heart visualisation, and arrhythmia classification visualisation results within Unity3D. Figure 7 presents a schematic diagram of the AR interface, highlighting key features including the real-time ECG data overlay, the interactive 3D heart model, and user controls.

A. 3D MODELLING AND ASSEMBLY OF THE HUMAN HEART

For the assembly of the 3D model of the human heart, we used BodyParts3D [50], a database of 3D anatomical structures that provides detailed information on anatomical entities. BodyParts3D is maintained by the Database Center for Life Sciences and was developed by Kousaku Okubo [51]. This resource allows users to select specific parts and embed them, offering a comprehensive tool for studying anatomical structures [50]. In our project, we utilised BodyParts3D as a kit to construct the 3D model of the human heart, which comprises 152 sub-objects (Figure 8). The challenge lay in assembling these 3D sub-objects into a cohesive structure. This required fitting the sub-objects together based on their shapes and patterns and accurately positioning them in 3D space. Figure 8 illustrates the step-by-step assembly process, highlighting the complexity and precision involved in creating a detailed 3D model of the heart.

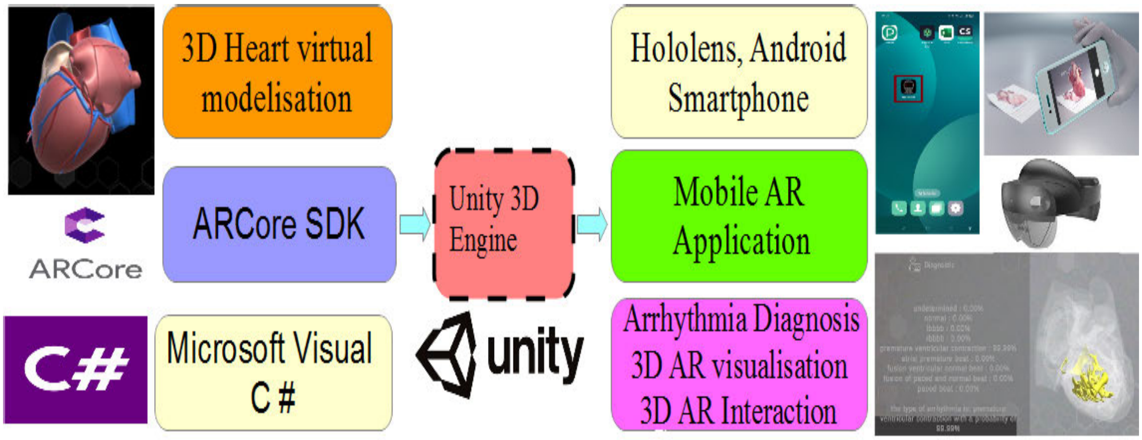


FIGURE 6. The block diagram of ArythmiAR platform.

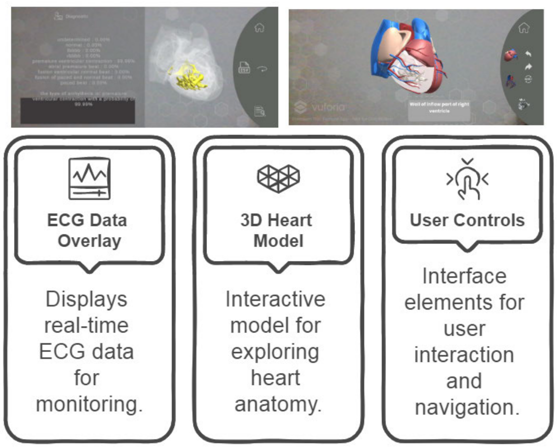


FIGURE 7. Features of the AR Interface for enhanced visualisation and interaction.

B. ArythmiAR: PLATFORM CONCEPTION FOR DIAGNOSIS RESULTS VISUALISATION AND INTERACTION

AR visualisation and interaction can significantly improve heart disease diagnosis and understanding by providing enhanced spatial understanding, personalised learning, real-time guidance during procedures, improved patient communication, streamlining diagnostic processes, and facilitating remote consultations and collaborations. AR creates immersive, 3D heart visualisations, allowing healthcare professionals to understand complex structural relationships and identify specific issues. It even improves patient engagement and education, helps in real-time advice and guidance during procedures, and promotes remote consultations among healthcare practitioners.

ArythmiAR platform incorporates advanced deep learning techniques for ECG classification, assuring efficient arrhythmias diagnosis through balanced techniques that handle class imbalance issues typically encountered in ECG datasets. This deep learning deployment is uniquely embedded within an AR environment, which not only improves the 3D heart model visualisation but also permits the real-time arrhythmia anomalies localisation and visualisation. This combination of 3D heart visualisation and AR-based diagnostic capabilities supplies medical practitioners and clinicians with a spatially and intuitive contextualised understanding of electric cardiac activity, a considerable advancement over traditional methods. Likewise, our platform presents interactive elements such as voice interaction and hand-tactile interaction, offering a user-friendly and immersive experience that is not attended in existing AR systems concentrated largely on visualisation. By integrating these features, our platform not only enhances the arrhythmia diagnosis accuracy and reliability but also improves the overall clinical workflow, making it a novel and comprehensive solution for cardiac care. The integration of deep learning, AR, and interactive technologies describes a noteworthy step forward in the field, presenting an effective approach and a more holistic for arrhythmia diagnosis and patient care.

To effectively illustrate the 3D heart models used in the ArythmiAR platform, we propose the inclusion of several detailed visual representations. These illustrations are designed to elucidate the anatomical precision, functional capabilities, and interactive features of the models within the AR environment.

1) Anatomical Precision of the 3D Heart Model: We provided a high-resolution, annotated 3D rendering of the heart model, including clearly labelled anatomical structures such as the ventricles, atria, aorta, pulmonary arteries, and valves. The use of colour-coding to differentiate cardiac regions and realistic textures to depict tissues such as the myocardium and pericardium has enhanced the model's anatomical accuracy, which is crucial for the precise location of arrhythmia anomalies.
2) 3D Heart Model with Highlighted Arrhythmia Anomalies: We offered an illustration of the 3D heart model

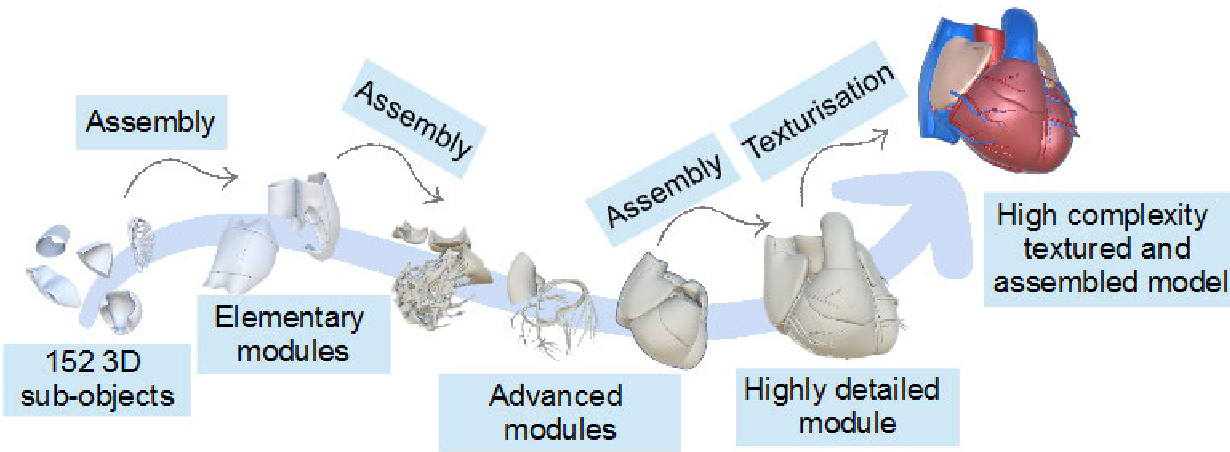


FIGURE 8. **3D Modelling and assembly of the human heart.**

highlighting specific regions associated with various types of arrhythmias, such as atrial fibrillation and ventricular tachycardia. We incorporated a dynamic element to visualise the propagation of electrical signals through the heart.

3) Interactive 3D Heart Model within the AR Environment: We conceived interactive AR functionalities where users can manipulate the model (e.g., rotating, zooming, slicing) and see how real-time ECG classification data is overlaid onto the model, illustrating the correlation between electrical activity and anatomical location.
4) Assembly Process of the 3D Heart Model: A step-by-step diagram as illustrated into figure 8 of the 3D heart model assembly process, detailing how different cardiac components are integrated into the complete model. Annotations describing each step, and visual progression are used to show the increasing complexity of the model.
5) Localisation of Arrhythmia Anomalies in the 3D Heart Model: A detailed view of the 3D heart model is provided to demonstrate the localisation of arrhythmia anomalies. We highlighted specific regions to indicate different types of arrhythmias, and include annotations that describe the type of arrhythmia.

This section introduces our application, ArythmiAR, which seamlessly integrates the capabilities of the Unity 3D Engine for 3D modelling [48], leverages ARCore to enhance the augmented reality experience [32], and utilises Visual Studio with C# for smooth application development [55]. This application represents a convergence of cutting-edge technologies, providing medical professionals with a diagnostic aid for arrhythmia, while offering a comprehensive and educational exploration of the complexities of the human heart. Figure 6 presents the project's block diagram, offering an overview of its architectural framework. For application development, we used a workstation equipped with two Intel Xeon (R) Silver 4114 processors (20 cores @ 2.199 GHz), 256 GB RAM, an NVIDIA Quadro P2000 GPU (5 GB VRAM), and 2TB HDD storage.

ArythmiAR enables medical professionals to explore cardiac arrhythmia diagnosis using a CNN-based model within a 3D virtual environment generated by Unity3D. The platform not only visualises arrhythmia classification results but also provides a 3D visualisation and localisation of the specific sub-region of the heart responsible for the anomaly. Users can interact with intricate details of the virtual heart in real-time, enhancing their understanding and knowledge retention by augmenting visual elements with definitions, technical details, and audio explanations for each heart component. The application seamlessly integrates virtual elements into the real world, allowing users to simulate medical scenarios for hands-on skill development. ArythmiAR comprises an introduction to 3D heart anatomy using AR, which displays and explains the different sub-regions of the heart. We conceive hand-tactile and voice interaction features, elevating the experience for medical professionals. With hand-tactile interaction, users can effortlessly navigate 3D heart models and manipulate visualisations, providing a truly hands-on experience. Voice interaction, powered by natural language processing, allows users to communicate with the application, streamlining their interactions and boosting overall efficiency. With voice commands and tactile hand-based interactions, including grabbing, resizing, rotating, and displaying objects, ArythmiAR provides an intuitive and immersive experience. Detailed visualisations and informative annotations further support the understanding of complex medical concepts, effectively bridging the gap between theoretical knowledge and practical application in the medical field. This section provides a comprehensive comparative analysis between ArythmiAR and several state-of-the-art AR applications in the realm of cardiac imaging

TABLE 9. Comparing our ArythmiAR platform with the state-of-the-art existing works.

Work	Platform/Device	Functionalities	Application
[7]	Android Smart phone	Visualisation, Interaction by Menu selection	Educational experience
[33]	Web application	Visualisation	Human Heart Anatomy Comprehension
[34]	Smartphones/ Tablets	Visualisation, Zoom in, zoom out, and rotate the 360° cardiac model along any axis	Learning sequence of activities connected to the cardiac cycle
[35]	Android Smart phone	Visualisation without interaction	Heart Anatomy teaching
[36]	Mobile App	Visualisation	Human Anatomy
[52]	3D hologram	Visualisation	diagnosis and surgical planning
[53]	Hololens	Navigation and visualisation	Endovascular aortic repair
[54]	AR HMD	Visualisation	Coronary artery disease diagnosis
ArythmiAR Our proposal	Android Smart phone	3D Heart visualisation, 3D Arrhythmia Anomalies visualisation Introduction to heart anatomy Arrhythmia Diagnosis Diagnosis Results Display Hand tactile Interaction, Voice Interaction,	Arrhythmia diagnosis based DL 3D Heart Anatomy Medical Practice

and anatomy education. It highlights the functionalities and applications offered by each platform or device, facilitating a better understanding of their respective strengths and applications. In contrast, ArythmiAR, our proposed platform, operates on Android smartphones and offers a comprehensive set of functionalities, including arrhythmia diagnosis results, 3D representation and localisation of the heart's specific sub-region responsible for the anomaly, an introduction to 3D heart anatomy, and features such as translation, rotation (zoom in/out, rotate, and translate along any axis), along with tactile and voice interaction. The comparison presented in this section highlights that while various existing AR applications focus on specific aspects such as visualisation, anatomy comprehension, or educational experiences, ArythmiAR distinguishes itself by offering a full suite of functionalities tailored to arrhythmia diagnosis through a deep learning-based approach and diagnosis 3D visualisation. Its integration of tactile and voice interaction, combined with advanced 3D diagnostic visualisations, positions it as a powerful tool for immersive and interactive medical education, particularly in cardiac-related fields.

Table 9 provides a comprehensive overview of the functionalities and applications of various augmented reality systems in the medical field, with a particular focus on cardiac applications. A key novelty of our proposed ArythmiAR platform is its integration of advanced features that go beyond mere visualisation, which is a common function in existing AR systems [7], [33], [34], [35], [36]. The comparison in Table 9 highlights the distinctiveness and advancements of our proposed ArythmiAR platform over existing state-of-the-art AR systems. While prior works such as [7], [33], and [34] primarily focus on visualisation and educational applications (e.g., heart anatomy comprehension and cardiac cycle learning), they lack advanced functionalities for medical diagnosis and interactive user engagement. Similarly, [52], [53], and [54] leverage AR for diagnosis and surgical planning, but their reliance on specialised hardware (e.g., 3D holograms, Hololens, or AR HMDs) limits accessibility and practicality. Unlike platforms that rely solely on visualisation [33], [35] or basic interaction methods [7], ArythmiAR offers a multifaceted approach by incorporating 3D heart visualisation, detailed visualisation of arrhythmia anomalies, and interactive elements such as hand tactile and voice interactions. These features enable a more immersive and informative experience for medical professionals, facilitating not only the understanding of heart anatomy but also the diagnosis of complex cardiac conditions. Moreover, ArythmiAR distinguishes itself by its application in arrhythmia diagnosis using deep learning (DL), a functionality not prominently featured in existing AR systems. While some works like [52] utilise 3D holograms for diagnosis and surgical planning and [53] employs Hololens for navigation and visualisation in endovascular aortic repair, they do not specifically target arrhythmia diagnosis. Similarly, [54] uses an AR head-mounted display (HMD) for diagnosing coronary artery disease but lacks the interactive and diagnostic capabilities

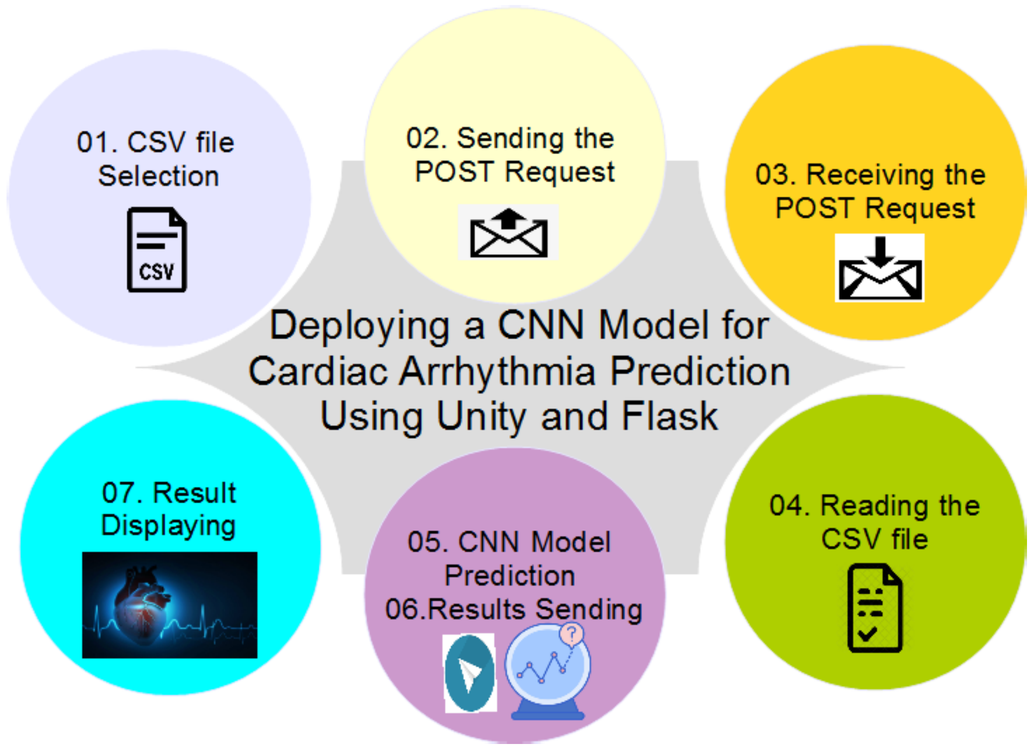


FIGURE 9. Schematic of CNN model deployment for cardiac arrhythmia prediction using unity 3D and flask.

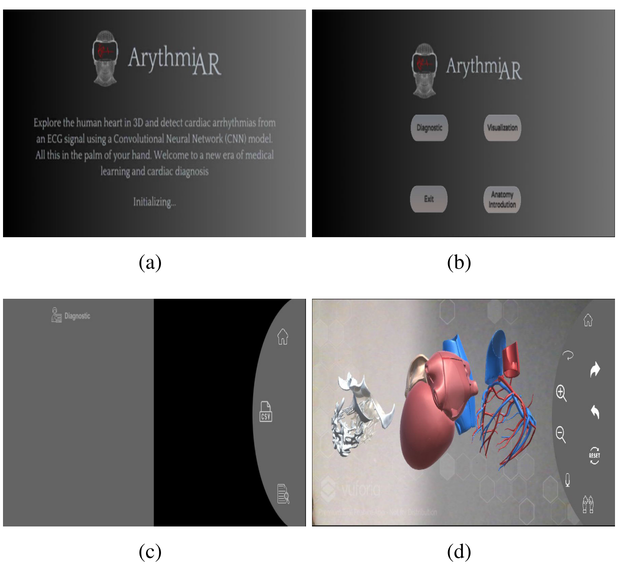


FIGURE 10. The ArythmiAR interfaces. (a) Homepage, (b) Main menu interface, (c) Diagnostic, (d) 3D Heart Anatomy Introduction.

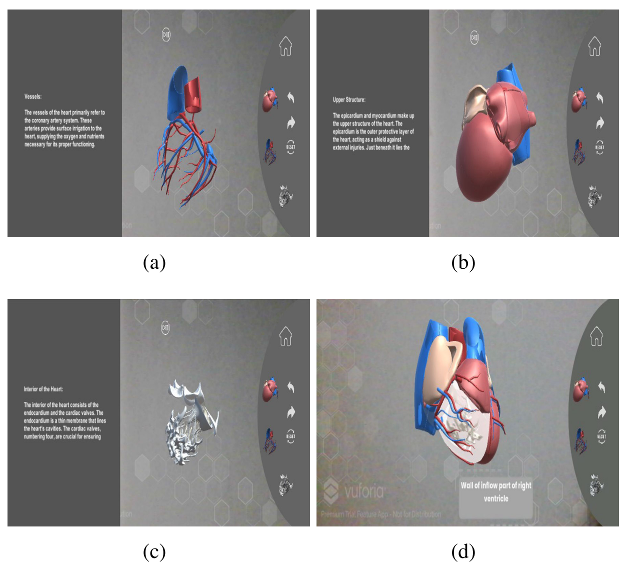


FIGURE 11. The ArythmiAR: 3D heart anatomy introduction. (a) Heart vessels, (b) Heart upper structure, (c) 3D Heart interior, (d) 3D Heart sub-region selection.

that ArythmiAR provides. Our platform's ability to localise and visualise specific heart regions responsible for arrhythmia anomalies, coupled with its interactive diagnostic tools, represents a significant advancement in AR-assisted cardiac care. Additionally, ArythmiAR's compatibility with Android smartphones enhances its accessibility, making it a practical tool for medical practice. This contrasts with systems that require specialised hardware such as 3D holograms [52] or AR HMDs [54], which may limit their widespread adoption. By combining advanced visualisation, interactive features, and deep learning-based diagnosis, ArythmiAR offers a comprehensive solution for arrhythmia detection and cardiac anatomy education, positioning itself as a cutting-edge AR

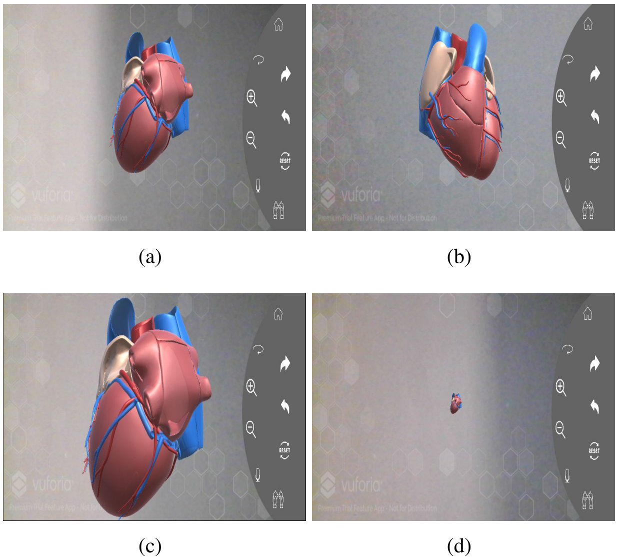


FIGURE 12. The ArythmiAR interaction functionalities. (a) Visualisation, (b) Rotation, (c) Zoom-in, (c) Zoom-out.

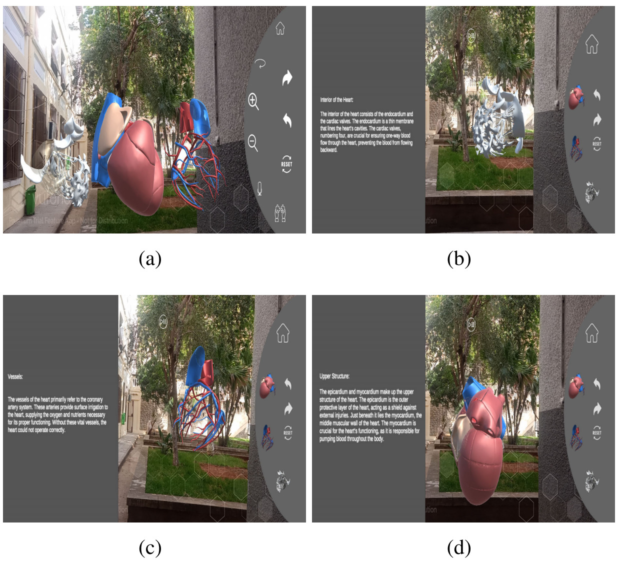


FIGURE 13. The ArythmiAR AR visualisation results. (a) AR Heart division, (b) AR Heart Interior, (c) AR Heart Vessels, (d) AR 3D Heart Sub-region selection.

system in the field of medical technology. This combination of diagnostic capabilities, interactive features, and accessibility represents a significant leap forward in AR-based medical applications, addressing both educational and clinical needs.

These groundbreaking enhancements empower medical professionals with a highly immersive, efficient, and intuitive tool for studying and treating medical conditions, including complex cases. ArythmiAR represents a significant leap forward in medical education and practice, offering a transformative learning experience that will benefit both current and future healthcare professionals.

C. DEPLOYMENT OF A CNN MODEL FOR CARDIAC ARRHYTHMIA PREDICTION IN THE UNITY 3D ENGINE

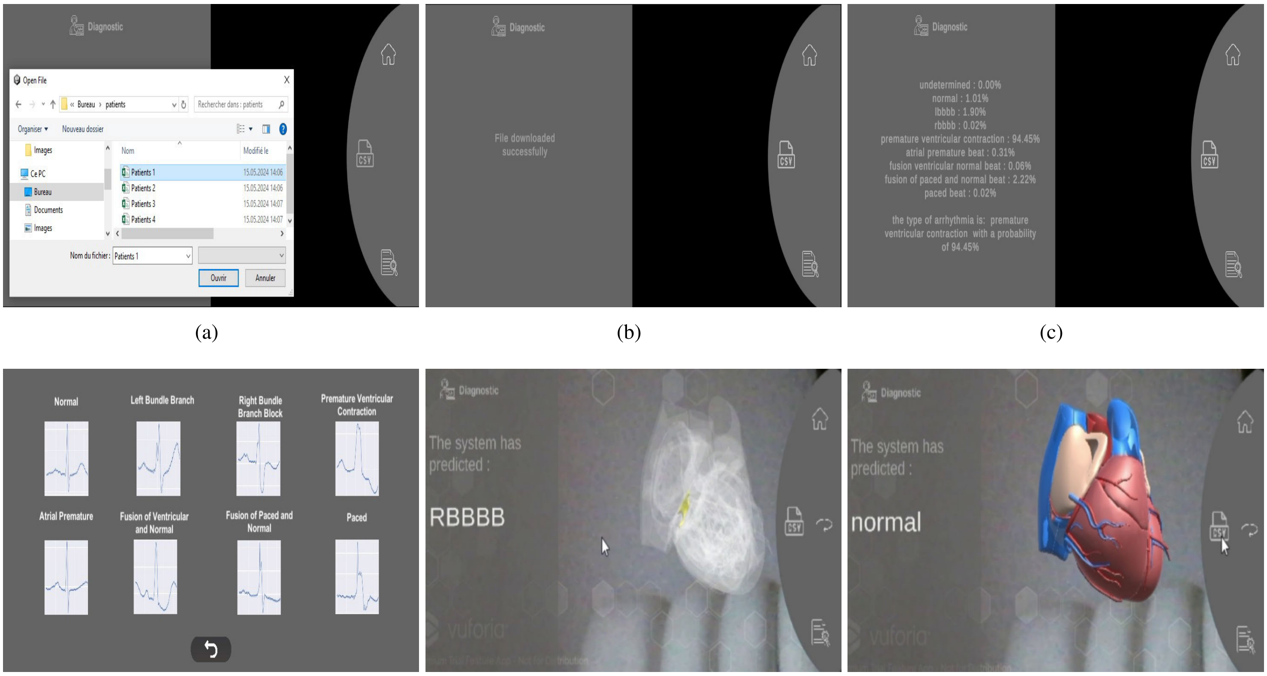
The choice of deploying the CNN-based model in our AR environment was based on a comprehensive evaluation of several factors, including model complexity, computational efficiency, and the specific requirements of real-time ECG classification in an AR setting. While the tabulated results in Table 6 and Table 7 indicate that the MLP-based model achieved slightly better performance metrics compared to the CNN-based model, it is important to consider the broader context of our deployment strategy. The CNN-based model was chosen for its architectural advantages in handling complex, high-dimensional data such as ECG signals. The CNN's ability to automatically learn and extract hierarchical features from raw data makes it particularly suitable for the nuanced patterns present in ECG waveforms. Additionally, the CNN's ability to generalise and adapt to variations in input data makes it more robust in clinical settings where ECG signals can vary significantly between patients and conditions. This robustness is crucial for maintaining consistent diagnostic performance in diverse clinical scenarios.

One of the main contributions of this work is the deployment of deep learning-based arrhythmia classification into a Unity 3D engine [48]. To achieve this, we opted for an alternative approach called ''Inference as a Service''. This method involves exposing a machine learning model as a web service, accessible via HTTP requests (figure 9). We used the Android SDK with API Level 33 (Android 13) for deployment and testing. We tested the application on a Redmi Note 11 Pro+ 5G smartphone. In our case, we use a Flask server to expose our deep learning model and generate predictions from CSV file data, following the process outlined below:

- CSV File Selection: The user selects a CSV file containing the digital ECG signal via a file selection dialogue in Unity.
- Send POST Request: Unity sends a POST request to the Flask server, passing the path of the selected CSV file.
- Receive POST Request: The Flask server receives the POST request and extracts the path to the CSV file.
- Read CSV File: The Flask server reads the specified CSV file and prepares the data for prediction.
- Deep Learning Model Prediction: The Flask server uses the extracted data to make a prediction using the deep learning model.
- Send Response: The Flask server sends the prediction results back to Unity.
- Display Results: Unity receives the response from the Flask server and displays the prediction results within the app.

D. DIAGNOSIS AUGMENTED REALITY VISUALISATION AND INTERACTION AND RESULTS

We have developed a comprehensive suite of innovative interaction and visualisation features for arrhythmia diagnosis.



(a) (b) (c)

(d) (e) (f)

FIGURE 14. **The ArythmiAR diagnosis results. (a) CSV File selection, (b) File downloading success, (c) CNN arrhythmia classification results, (d) Arrhythmia type, (e) Right bundle branch block beat anomaly case "RBBBB", (f) Normal case.**

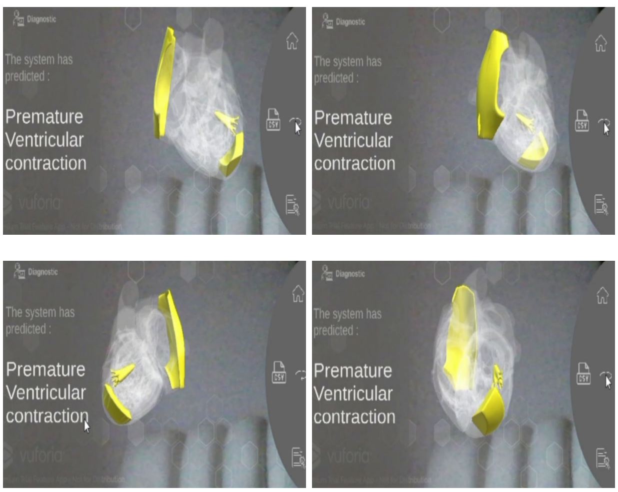


FIGURE 15. **The ArythmiAR diagnosis visualisation and interaction results: Premature ventricular contraction case.**

These include CNN-based arrhythmia classification results deployed into the Unity 3D engine, a detailed 3D representation and localisation of the heart's specific sub-region responsible for the arrhythmia anomaly, and an introduction to 3D heart anatomy. The platform also offers advanced interaction capabilities, including translation, rotation (zoom in/out, and manipulation along any axis), as well as tactile and voice command support. Figure 10 showcases the user interface of the platform: the home page (Figure 10-a), the main menu (Figure 10-b), the arrhythmia diagnosis interface (Figure 10-c), and the interface for the 3D heart anatomy introduction (Figure 10-d). These features allow users to manipulate and interact with the 3D heart model precisely and intuitively, permitting in-depth exploration and understanding of cardiac anomalies. By including such functionalities, our platform bridges the gap between theoretical understanding and practical knowledge, improving both the medical learning experience and the diagnostic process.

Figure 11 presents the visualisation results of the 3D heart anatomy introduction, featuring specific annotations and detailed explanations for each heart sub-region. The figure also highlights the interactive and visualisation functionalities, allowing users to engage with the 3D heart model in real-time. These interactions, such as zooming, rotation, and translation, provide a complete understanding and interpretation of the heart's anatomical structure, making it easier to recognise and comprehend the complexities of each region. The annotations are designed to enhance learning by presenting precise, accessible explanations directly linked to the related heart components, further bridging the gap between theoretical knowledge and practical medical education. These interaction features can be seamlessly activated in two distinct modes: vocal commands and hand-tactile commands, ensuring accessibility and user-friendliness across different preferences and capabilities (figure 12).

Figure 13 showcases the augmented visualisation of the designed scene and the 3D heart model in the augmented reality environment. The model is accompanied by interactive features that permit users to explore, investigate and manipulate the heart's anatomy. In our application, ArythmiAR, we implemented 3D augmentation using ARCore technology. Additionally, the platform provides detailed AR explanations for each sub-region of the heart, enhancing the educational experience. This interactive 3D rendering enables users to acquire a deeper understanding of the heart's structure and function, making it a practical tool for both clinical applications and medical training.

Figure 14 illustrates the deployment of the CNN-based arrhythmia classification into the 3D engine. It begins with the CSV ECG file data uploading, as shown in Figures 14-a and 14-b. Figure 14-c displays the classification results produced by the CNN model, while Figure 14-d presents the identified cardiac arrhythmia types detected by our application. In Figure 14-e, a 3D representation and localisation of the heart's specific sub-region, responsible for a Right Bundle Branch Block beat case (RBBBB), is shown, providing users with a visual understanding of the anomaly. In contrast, Figure 14-f depicts a normal case, where the classification results indicate that the ECG is within normal parameters. Additionally, Figure 15 offers a 3D visualisation of a Premature Ventricular Contraction case, allowing users to observe and interact with the affected sub-region in real-time. These results demonstrate how the integration of arrhythmia CNN-based diagnosis using ECG with 3D localisation and visualisation offers a more interactive, comprehensive, and immersive experience. This enables users not only to view but also to localise and manipulate the heart's sub-regions associated with various arrhythmia cases. The platform's real-time interactivity enhances the understanding and interpretation of different cardiac conditions, making it an effective tool for both diagnostic support and medical training. The abbreviation into figure 14 correspond respectively to: Right bundle branch block beat (RBBBB), Left bundle branch block beat (LBBBB).

While our proposed ArythmiAR platform demonstrates significant advancements in arrhythmia diagnosis and 3D visualisation, it has certain limitations that need to be addressed. First, the system currently relies on pre-processed ECG data, which may not fully capture real-time cardiac variations in a clinical setting. Second, the class imbalance in the dataset, although mitigated through balancing techniques, may still affect the generalisability of the deep learning models to diverse patient populations. Third, the platform's interactive features, such as hand tactile and voice interaction, require further optimisation to ensure seamless usability across different devices and user environments. Finally, the anatomical 3D model, while detailed, could benefit from additional precision and contextual information to better support clinical decision-making.

V. CONCLUSION AND FUTURE WORK

This paper addresses the automatic diagnosis of cardiac arrhythmias to support both medical practice and education. We propose a platform called ArythmiAR, which integrates augmented reality technology and deep learning-based classification to provide a user-friendly solution. We anticipate that this innovative tool will significantly enhance the medical experience by offering aspiring medical professionals a deeper understanding of cardiac physiology through 3D visualisation of heart anatomy. This includes identifying and localising the specific heart sub-regions responsible for arrhythmia anomalies, as well as improving proficiency in the classification and diagnosis of arrhythmias. To evaluate the impact of our proposed rebalancing techniques on deep learning models used for ECG classification, we conducted extensive experiments. Despite the apparent simplicity of the models employed, such as MLP and CNN, we achieved remarkable performance on the PhysioNet MIT-BIH Arrhythmia dataset. These results underscore the effectiveness of our proposed rebalancing strategies. In addition, we developed an affordable and user-friendly AR application for automated arrhythmia classification using ECG data. The ArythmiAR platform simplifies the process of locating and visualising the heart, offering immersive 3D visualisation and interactive features. This empowers medical professionals with a realistic and immersive tool, enabling precise diagnosis and visualisation of classification results to aid in the formulation of effective treatment plans. Future research should focus on ensuring the confidentiality and integrity of ECG data within the AR ecosystem, which is especially critical in clinical contexts. These goals can be achieved by adhering to legal compliance and ethical standards, and by fostering collaborative partnerships among software developers, AR specialists, and healthcare professionals. Future research will concentrate on addressing the current limitations and enhancing the platform's capabilities to better serve clinical needs. Key directions include developing advanced techniques for class imbalance management in ECG datasets to ensure robust performance across all arrhythmia types and implementing real-time ECG visualisation to allow healthcare professionals to dynamically monitor cardiac variations during diagnosis. Additionally, further refinement of AI algorithms is essential to improve diagnostic accuracy, particularly for rare or complex arrhythmias. Conducting extensive evaluations of the classification algorithms and AR applications in real-world clinical settings will be crucial to validate their practicality and effectiveness. Enhancing user interaction features is another important area, such as enabling physicians to insert personalised remarks and observations for each patient and adding download and print functionalities for diagnostic reports to improve clinical documentation flexibility. Furthermore, anatomical enrichment of the 3D heart model, by incorporating more precise textual and auditory information, will also improve the understanding of cardiac structures and their role in arrhythmias. Finally, the platform should continuously collect and integrate user feedback from healthcare professionals and patients to refine the user interface and adapt the system to their specific needs, ensuring it remains a valuable and user-centric tool in clinical practice.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Artificial Intelligent agents, such as ChatGPT3 or Grammarly4 have been used to improve the quality of written English language and grammatical error corrections.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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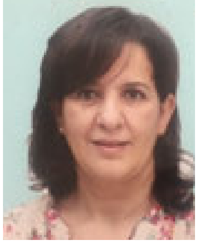

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