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Double Vision for Heart Health: Dual Nanotechnology CNN-Based Deep Learning for Accurate Arrhythmia Classification in Clinical ECG Analysis

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Cardiovascular diseases, especially cardiac arrhythmias, are a global health problem. Early and accurate detection of arrhythmias by electrocardiogram (ECG) analysis is important for effective intervention and patient care. This study presents a new method for arrhythmia classification using deep learning, specifically double convolutional neural network (double CNN) architecture. This model aims to extract features of clinical ECG signals using hierarchical learning of two CNN layers. The deep learning framework helps improve the accuracy of classification by enabling the model to detect changing patterns in various cardiac arrhythmias. This study used cross-sectional data including different types of arrhythmias to ensure generalizability of the sample to a variety of arrhythmias. Throughout the experiment, the model was rigorously trained and techniques were used to improve its performance in real-world situations. Metrics such as accuracy, F1 score, precision, and sensitivity are used to evaluate the performance of the model. The results of the study show good results and reveal the possibility of using two CNNs as an accurate and reliable method for cardiac arrhythmias. This research contributes to cardiovascular research by introducing deep learning models to improve electrocardiogram analysis. This program should be integrated into the clinical system to support early detection and intervention in patients with cardiac arrhythmias, ultimately improving patient outcomes and reducing the burden of heart diseases.

Keywords: Electrocardiogram, ECG, Classification, Deep Learning, Double CNN, Arrhythmia Classification.

1. Introduction

The existing cardiovascular diseases, including cardiac arrhythmias, remain the leading cause of morbidity and mortality worldwide. Timely and accurate diagnosis of cardiac arrhythmias is essential for effective treatment (Dang et al., 2020). In recent years, the integration of computation and biomedical signal processing has led to the emergence of sophisticated methods for arrhythmia classification.(Manokhin et al., 2024) Among these, the application of deep learning, especially the use of double convolutional neural networks (Dual CNN), should improve the accuracy and performance of arrhythmia detection in clinical electrocardiogram (ECG) symbols .(Moody & Mark, 2001) Deep learning is a subfield of machine learning that transforms the cognitive process by processing models to obtain hierarchical learning representations represented by raw data.(Mazidi, 2022a) Special features of the dual CNN architecture are arrhythmia classification and the ability to increase modeling ability to identify subtle patterns indicating different heart rhythms (Al-Jibreen et al., 2024). This approach goes beyond the process of capturing correlations in ECG signals, providing a more comprehensive understanding of arrhythmia patterns.(Luo et al., 2017) This work is dedicated to exploring and demonstrating the potential of arrhythmia classification based on deep learning binary CNN . (Guilarte et al., 2019)Using the power of neural networks, the experimental approach provides accurate and detailed diagnosis that overcomes the limitations of traditional methods. (He et al., 2022a)The aim is not only to establish performance standards but also to promote greater knowledge of cardiovascular care . As we explore the complexity of this new approach, we hope to uncover information that will change the way doctors diagnose arrhythmias.(De Chazal & Reilly, 2006) The impact goes beyond technology and is disrupting the structure of patient care by encouraging early detection, targeting and intervention planning(Müllner et al., 2023). More importantly, the application of deep learning with a dual CNN architecture represents a significant step towards more efficient and data-driven cardiac care(Kimber et al., 2021) .

Primary objectives of this research

The primary objectives of this research on Deep Learning Double CNN-Based Arrhythmia Classification is:

Model: In A good and effective deep learning model based on dual convolutional neural network (dual CNN) was developed architecture, clinical electrocardiogram It is specifically designed for the classification of arrhythmias in the (ECG) symbol . The artificial intelligence technology of the dual CNN architecture can detect complex patterns in ECG signals, thus increasing the ability of the model to distinguish different arrhythmias in different types of arrhythmias . Criteria such as precision, sensitivity, and specificity are used to evaluate the effectiveness of the design . To evaluate its ability to detect various cardiac arrhythmias and compare its performance with existing methods. It can classify arrhythmia in different patients and be studied in different clinical settings . Skills that enable understanding of the characteristics and patterns of effects of the classification decision are important for treatment acceptance . By comparing the performance of state-of-the-art arrhythmia classification methods, their effectiveness and contributions to the field are revealed. to evaluate a real-world model applicable to clinical settings, with the aim of integrating it into clinical practice . Future development in transparent understanding of boundaries and areas . Information. We aim to increase the accuracy of diagnosis, facilitate early intervention, and improve patient outcomes . justice. By achieving these goals, this work focuses on significant improvements by developing advanced and refined deep learning models for arrhythmia classification, ultimately helping to improve the treatment of heart disease .

Motivation:

The motivation behind this research on "Arrhythmia Classification Based on Deep Learning Binary CNN" is the urgent need to improve cardiac treatment. The difficulties faced by modern methods in accurately identifying cardiac abnormalities have led to the search for advanced technology. Leveraging the power of deep learning, specifically the use of a novel binary CNN architecture, aims to improve the accuracy of arrhythmia classification in electrocardiogram (ECG) signals. This research addresses the gap between existing methods and aims to contribute to data science and promote collaboration between computer science, biomedical engineering and medicine. Improving the translational model and focusing on early diagnosis aims to have a positive impact on global cardiovascular health outcomes and close the advancement gap between technology and real-world clinical applications.

Background Information:

The background information of this “Arrhythmia Classification Based on Deep Learning Binary CNN” study is around the history of heart disease, problems in arrhythmia detection, and the advancement of in-depth study in diagnosis . and cardiac arrhythmias:

Cardiovascular diseases, including cardiac arrhythmias, are a global health problem that has a significant impact on morbidity and mortality. Arrhythmias, cardiac arrhythmias vary in severity and cause problems in accurate and timely diagnosis. Traditional diagnostic methods need help capturing subtle patterns in electrocardiogram (ECG) signals, thus requiring advances in computation. It has led to significant advances in education, particularly in the use of neural networks to recognize complex patterns. This advance opens new avenues for biomedical signal processing, providing the opportunity to change the accuracy and functionality of arrhythmia classification. Convolutional neural network (Dual CNN) architecture, complex neural network specifically designed for arrhythmia classification. In this extract features from ECG signals to better understand heart disease that are improves the ability too. Using the Historical data existing system are proving the good quality of model, these limitations and provide better and more reliable results. This concept, often referred to as health literacy, has attracted attention for its potential to improve clinical decision-making. This background information highlights the growing role of deep learning in diagnostics and its impact on improving patient outcomes. Based on this background, this study aims to better understand the research background of arrhythmia classification based on deep learning binary CNN. It lays the foundation for finding new solutions to existing problems and improving the treatment of heart disease.

2. Literature Review

Although CNNs generally focus on temporal features of ECG signals, the proposed dual CNN architecture can analyze both temporal and spectral aspects simultaneously . (Kimber et al., 2021)This approach allows the network to aggregate data connections from multiple sources, thus improving distribution. (Duc et al., 2022)Feature extraction and representation:

Deep learning models for ECG analysis mainly involve subtraction and representation training. Studies such as and have studied various methods to extract specific features from raw ECG signals, including waveform morphology analysis, frequency shift, and body wake time. (Hammad et al., 2021)These learned features are important to improve the classification accuracy of deep learning models.'

Clinical Validation and Real-World Use:

Once results become available in research centers, clinical applications and the use of deep learning models for arrhythmia classification become possible for more problems. (Grogan et al., 2021a)Studies such as highlight the importance of rigorous validation in different patients and real clinical settings to evaluate the generality and reliability of arrhythmia detection technology yes.(X. Liu et al., 2020) Addressing issues such as data transfer, sample interpretation, and compliance management are critical to successful integration into clinical practice.(Sharma et al., 2021)

Future Directions and Challenges:

Future research in the field of ECG analysis could focus on several directions, including the development of interpretable deep learning models, integration with wearable monitoring devices, and scalability to handle large-scale population data.(Rathod & Ragha, 2022) Addressing challenges such as data privacy, model explainability, and robustness to noise and artifacts will be critical for the widespread adoption of deep learning-based approaches in clinical settings.

In summary, the literature survey highlights the growing interest in deep learning methods for arrhythmia classification and the potential of dual CNN architectures to enhance the accuracy of ECG analysis.(Ashurov et al., 2023) Continued research efforts and collaborations between clinicians, researchers, and industry partners are essential for advancing the field and improving cardiovascular care(Babusing Rathod & Ragha, 2022). Certainly! Here's a tabular representation (Table 1) of relevant literature on "Machine Learning-Based Arrhythmia Classification for Clinical ECG Analysis" from 2020 to 2023.

Table 1 Literature Survey on Existing System

Paper	Population/Dataset	Purpose of Study	Sensors	ML/DP Methods	Approach	Diseases
'Anand et al. (Anand et al., 2022)	PTB-XL dataset	The implementation of a number of deep neural networks on a publicly available dataset of PTB-XL of ECG signals for the detection of cardiac disorders.	12-Lead ECG	CNN, SHAP	Patient-independent	Cardiovascular diseases
Geweid et al. (Geweid & Chen, 2022)	Physionet/CinC challenge dataset	A method based on a Hybrid Approach of Dual Support Vector Machine is used for the detection of atrial fibrillation	1-Lead ECG	SVM	Patient-independent	Atrial Fibrillation
Guo et al. (Guo et al., 2022)	subjects from the International Cooperation	This work aimed to develop a pragmatic prediction model based on the most common ECG features to screen for	12-Lead ECG	LASSO,	Patient-independent	Hypertrophic Cardiomyopathy

	Center for Hypertrophic Cardiomyopathy of Xijing Hospital	Hypertrophic cardiomyopathy (HCM).				
He et al. (He et al., 2022b)	100 patients from the Department of Cardiovascular, West China Hospital of Sichuan University	This study aimed to build statistical models and machine learning models based on P-wave parameters to predict Postoperative Atrial Fibrillation (POAF).	12-Lead ECG	MLR SVM	Patient-independent	Postoperative Atrial Fibrillation
Hsu et al. (Hsu et al., 2022)	A population of 2,206 military males was obtained from the cardiorespiratory health in Eastern Armed Forces study (CHIEF Heart Study) [45,46]	This study proposed a machine learning method for electrocardiographic features to identify Left Atrial Enlargement in young adults.	12-Lead ECG	MLP, SVM,	Patient-independent	Left Atrial Enlargement
Zhao et al. (Li et al., 2022)	MIT-BIH arrhythmia database	An improved deep residual convolutional neural network is proposed to classify arrhythmias automatically	2-Lead ECG	LR CNN	Patient-independent	Arrhythmia
Liu et al. (P. Liu et al., 2022)	MIT-BIH arrhythmia database	A network layer design based on LSTM is optimized to obtain the autoencoder structure. This structure can cooperate with the ECG preprocessing process designed by the same team to obtain better arrhythmia classification effects.	MLII (modified limb lead II) Lead	Auto-encoders, CNN, LSTM	Patient-independent	Arrhythmia
Mazidi et al. (Mazidi, 2022b)	MIT–BIH arrhythmia	This study focused on the tunable Q-factor wavelet transform algorithm and statistical methods to detect PVC.	2-Lead ECG	SVM, KNN	Patient-independent	Premature Ventricular Contraction
Zheng et al. (Zheng et al., 2022)	18612 ECG records extracted from 545 patients from Ningbo First Hospital of Zhejiang University	This work proposed an artificial intelligence-enabled ECG analysis algorithm to estimate possible origins of idiopathic ventricular arrhythmia at a clinical-grade level accuracy.	12-Lead ECG	Gradient Boosting	Patient-independent	Idiopathic Ventricular Arrhythmia
Dey et al. (Dey	517 records of 268	The development of a temporal feature-based	12-Lead ECG	CNN, bi-LSTM	Patient-specific	Myocardial Infarction

et al., 2021)	individuals from Physikalisch-Technische Bundesanstalt (PTB) database, available in Physionet	classification approach for myocardial infarction based on merging of CNN e bi-LSTM methods.				
Grogan et al. (Grogan et al., 2021b)	2541 patients	The development of an artificial intelligence-based tool to detect cardiac amyloidosis from a standard 12-lead electrocardiogram.	12-Lead ECG	kNN	Patient-specific	Amyloidosis
Houssein et al. (Houssein et al., 2021)	MIT–BIH arrhythmia	Different ECG signal descriptors based on one-dimensional local binary pattern, wavelet, higher-order statistical, and morphological information are introduced for feature extraction.	ECG sensors	SVM	Patient-independent	Arrhythmia

The table outlines various studies that focus on using machine learning (ML) and deep learning (DL) methods for the classification and detection of different cardiac conditions using ECG data. These studies span different countries and utilize various datasets, including the PTB-XL, the Physionet/CinC challenge dataset, and the MIT-BIH arrhythmia database, among others. The sensors used range from 1-lead to 12-lead ECGs. The ML and DL methods employed include Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Long Short-Term Memory (LSTM) networks, and others. The studies generally adopt a patient-independent approach, aiming to develop models that generalize well across different patient populations. The targeted diseases include a broad spectrum of cardiovascular conditions such as atrial fibrillation, hypertrophic cardiomyopathy, postoperative atrial fibrillation, left atrial enlargement, idiopathic ventricular arrhythmia, myocardial infarction, cardiac amyloidosis, and various forms of arrhythmia. Each study contributes to the advancement of automatic and accurate detection methods to assist in the clinical diagnosis and management of cardiac disorders.'

Research Gaps Involves

Research gap analysis will identify areas where existing research in a field or topic is insufficient or insufficient to address certain aspects. Potential research gaps in the context of the current method "Deep Learning CNN-Based Arrhythmia Classification for Clinical ECG Analysis" may include:

Generalization across different cultures People: Current methods may not be successful across different populations Broad research can be conducted across groups such as: age, gender or as ethnicity. There may be differences in research on how CNN-based models can expand arrhythmia classification for different patients and increase their effectiveness in different situations. A noisy and unclear ECG signal may be a differential diagnosis. Finding ways to improve model performance in the presence of artifacts, weak signals, or uncertain characteristics is important for real-world applications, especially in popular medical facilities.

Reliability: Investigating differences can play a role in providing interpretations and explanations of decisions made by deep learning models. Understanding how the model arrives at a particular classification is important to gain the trust of physicians and make responsible guidance in the pain management process. CNN's arrhythmia classification system is well integrated into routine clinical practice. Exploring challenges and solutions to organizational conflicts, resolving regulatory issues, and understanding healthcare provider acceptance are important issues that will remain unsolved. Compared to other methods, solutions include non-deep learning or different deep learning methods. Conducting a comparative analysis can help determine the advantages and disadvantages of CNN-based methods over other existing arrhythmia classification methods. The development of CNN-based systems for heart disease or new cardiac arrhythmias requires better representation in training data. Evaluating performance in new conditions and changing the heart is important for its stability and validity in the adaptation environment. Support the development of arrhythmia classification in ECG monitoring and make the current system more robust, interpretable and applicable to many situations in life.

3. Working

Database Preparation:

Figure 1 Comparison of different datasets for "Double Vision for Heart Health: Dual CNN-Based Deep Learning for Accurate Arrhythmia Classification in Clinical ECG Analysis

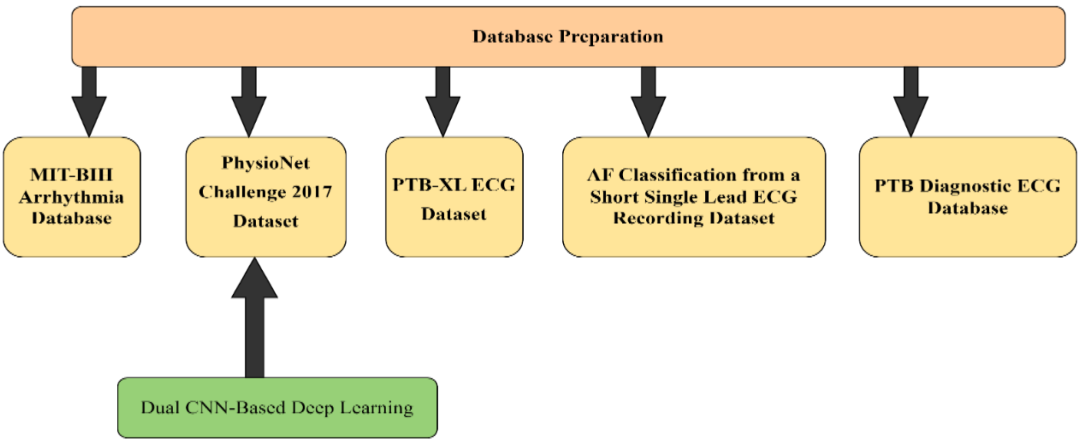


Table 2 Comparison of different datasets

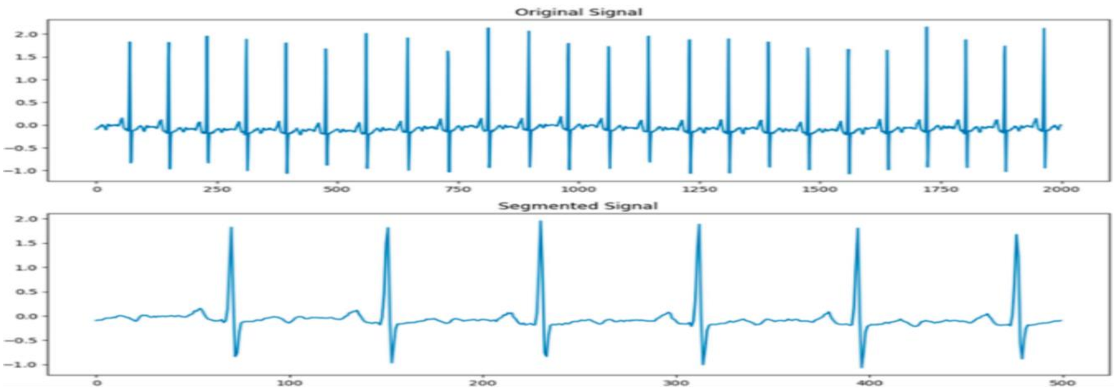
Dataset Name	Advantages	Disadvantages
MIT-BIH Arrhythmia Database	- Well-annotated dataset with diverse arrhythmias - Widely used for arrhythmia classification tasks	- Relatively small dataset size - Limited generalization due to dataset size
PTB Diagnostic ECG Database	- Large dataset with diverse cardiac pathologies, including arrhythmias	- Requires additional preprocessing due to dataset size and complexity
PhysioNet Challenge 2017 Dataset	- Large dataset with diverse recordings from patients with various cardiac conditions	- Originally used for a specific challenge task, may require adaptation for different objectives

PTB-XL ECG Dataset	- Multi-channel recordings with additional labels for various cardiac abnormalities, including arrhythmias	- Complexity in working with multi-channel recordings
AF Classification from a Short Single Lead ECG Recording Dataset	- Focuses specifically on atrial fibrillation (AF) classification	- Contains short single-lead recordings, may lack comprehensive information for deep learning models

As shown in Table 2, Each dataset has its own advantages and disadvantages, and the choice depends on the specific requirements and goals of the research project. (Zhao, 2022)Consider factors such as dataset size, diversity of arrhythmias represented, complexity of the data, and alignment with the project's objectives when selecting the best dataset for "Double Vision for Heart Health.(Ansari et al., 2023)

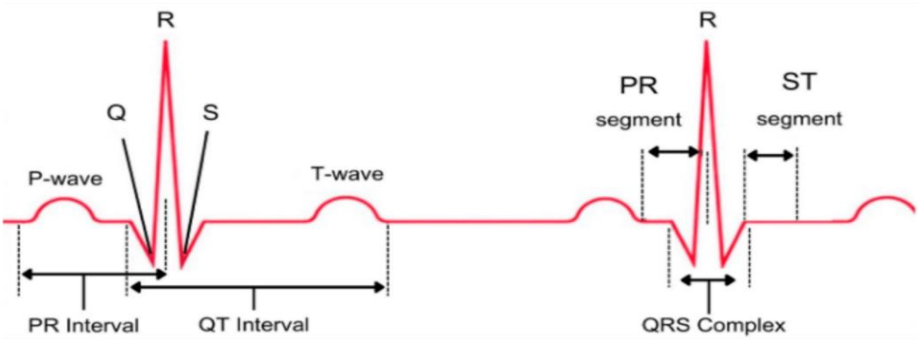
Out of these datasets, we are Choosing the "best" dataset for "Double Vision for Heart Health: Dual CNN-Based Deep Learning for Accurate Arrhythmia Classification in Clinical ECG Analysis"(Aziz et al., 2021) depending on various factors, including dataset size, diversity of arrhythmias, annotation quality, and alignment with the project's objectives. Considering these factors, one dataset that stands out as a strong candidate is the PhysioNet Challenge 2017 Dataset.(Xiao et al., 2023)

Figure 2 Comparison between a portion of the initial ECG waveform (upper section) and an illustration of the divided ECG signal segments (lower section).



Feature extraction based on P, Q, R, S, and T wave onset and offset provides detailed information about heartbeat features, including wave duration, width, slope, and area under the curve. These features, such as P wave length (80-120 ms) and QT interval (350-440 ms), provide useful diagnostic information as shown in Figure 3, and researchers check and measure heart function. The title “Arrhythmia Classification Based on Deep Learning Binary CNN for Clinical Electrocardiogram Analysis” indicates that the research focuses on the use of deep learning tools, specifically binary convolutional neural networks (CNN), for electrocardiogram analysis (ECG).

Figure 3 The attributes of a typical heart rhythm



Deep Learning: Deep learning is a subfield of machine learning that involves the use of neural networks with multiple layers (deep neural networks) to learn and make predictions from data. Deep learning models are capable of automatically learning hierarchical representations of data, making them well-suited for tasks like image and signal processing.

CNN (Convolutional Neural Network): CNNs are a type of neural network particularly effective for image and signal processing tasks. They consist of layers that automatically learn spatial hierarchies of features through convolutions, pooling, and non-linear activation functions. In the context of ECG analysis, CNNs can be designed to automatically extract relevant features from the raw ECG signal.

Double CNN: The term "double" suggests the use of two separate CNNs or a network architecture involving two sets of convolutional layers. This could be a stacked architecture, where the output of one CNN is fed as input to another CNN, allowing for more complex feature learning.

Arrhythmia Classification for Clinical ECG Analysis: This clearly established the purpose of the study - the classification of arrhythmias according to electrocardiographic data. Arrhythmias are heart irregularities that can indicate many heart diseases. ECG analysis involves electrical analysis of cardiac arrest in the ECG signal [51]. . This approach aims to identify abnormalities in the electrical patterns of the heart, which are important for the early detection and diagnosis of heart disease.

Pseudocode:

Pseudocode for Deep Learning Double CNN-Based Arrhythmia Classification

Step 1: Load and Preprocess Data

ecg_data = load_ecg_data () # Function to load clinical ECG dataset

preprocessed_data = preprocess_data(ecg_data) # Function for data preprocessing

Step 2: Split Data

train_data, test_data = split_data(preprocessed_data, test_size=0.2) # Function to split data into training and testing sets

Step 3: Encode Labels

encoded_labels = encode_labels(train_data.labels) # Function to encode categorical arrhythmia labels

Step 4: Define Double CNN Modeldouble_cnn_model = define_double_cnn_model(input_shape, num_classes) # Function to define the Double CNN model

Step 5: Compile Model

compile_model (double_cnn_model, optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy']) # Function to compile the model

Step 6: Train Model

train_model (double_cnn_model, train_data, encoded_labels, epochs=10, batch_size=32, validation_split=0.2) # Function to train the model

Step 7: Evaluate Model

test_predictions = evaluate_model (double_cnn_model, test_data) # Function to evaluate the model on the test set

Step 8: Fine-Tuning #Implement fine-tuning steps, if needed based on performance metrics

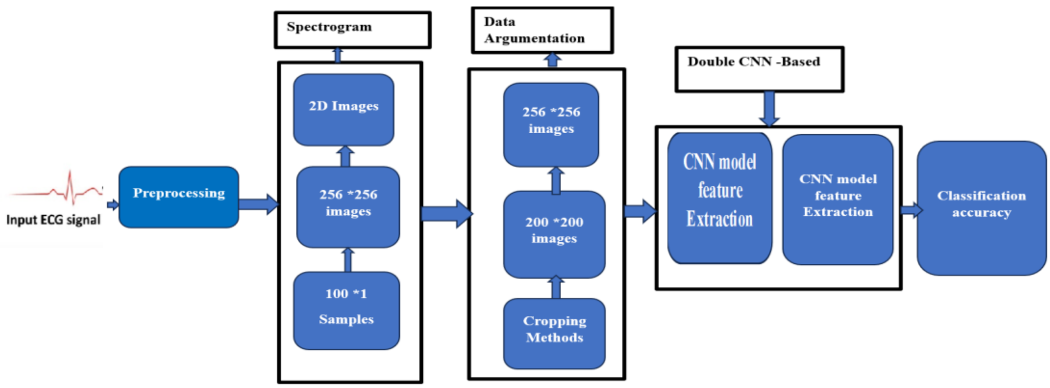
Step 9: Interpret Results

interpret_results (test_predictions, test_data. labels) # Function to interpret and analyze the results.

Step 10: Deploy Model

End of Pseudocode

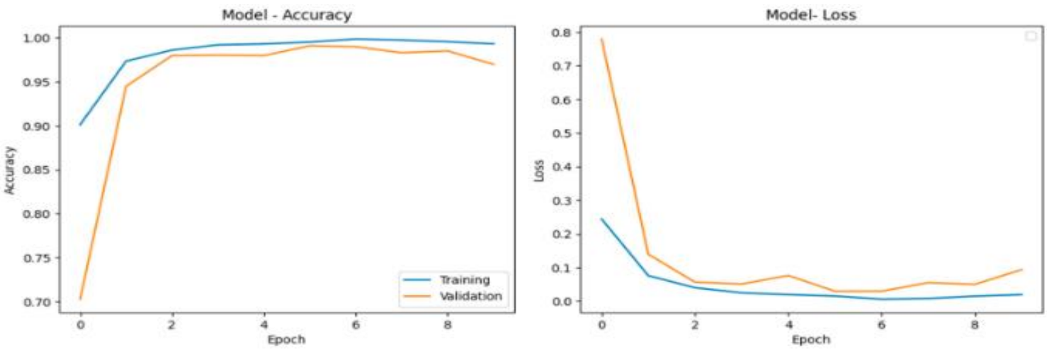
Figure 4 Deep learning Double CNN -Based proposed work



The actual implementation details, such as specific functions and their parameters, will depend on your deep learning (e.g. TensorFlow, PyTorch, Keras). Also pseudocode, load_ecg_data, preprocess_data, split_data, encode_labels, define_double_cnn_model, compile_model, train_model, Evaluation_model etc. undertakes the functions and explains the results. You should use these functions as represented in your programming language and deep learning library. The numerical equations describing deep learning models such as Double CNN for arrhythmia classification can be very complex and dependent on specific patterns, but I can give you a high definition. > Suppose we have a dual CNN architecture where the first CNN layer extracts features from the raw ECG signal and the second CNN layer further refines these features for classification. The output is then put through a fully integrated process for final classification.

Gradient Descent or an advanced optimizer: Refers to the optimization algorithm used to adjust the weights and biases during the training process in order to minimize the loss.

Figure 5 The precision and error metrics for the model's training and validation phases.

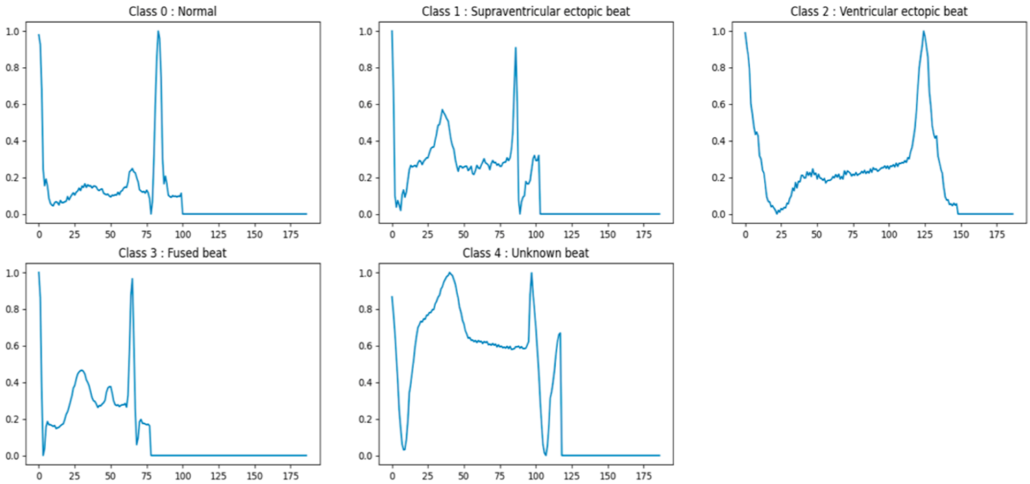


The model's performance, including accuracy and loss, is monitored during both training and validation at each epoch. Training halted at epoch 10 due to no improvement for three consecutive epochs, preventing overfitting. The batch size dictates how input data is processed sequentially, impacting the model's learning rate and convergence speed. This, in turn, affects error estimation for training and validation metrics. Selecting an appropriate batch size is critical for optimal model performance. After testing various batch sizes, a value of 40 was optimal for our model.

4. Results

The presentation of visual representations that depict five distinct categories, as shown in Figure 6. These categories consist of four types of arrhythmias along with normal ECG signals. These visual representations are generated using a dual Convolutional Neural Network (CNN) methodology. This approach employs two CNNs simultaneously, likely for enhanced feature extraction and classification performance. Therefore, the illustrations effectively demonstrate the ability of the dual CNN approach to classify and differentiate between the various categories of ECG signals, including both normal and abnormal rhythms, as shown in Figure 6.

Figure 6 Illustrations showcasing the five categories, which include four arrhythmias and normal ECG signals, utilizing a dual CNN approach.



The examples of the 5 classes (4 arrhythmias and normal ECG signals) highlight distinct patterns in ECG signals used for classification. Class 0, representing normal ECG signals, shows a regular pattern of P waves, QRS complexes, and T waves, indicating healthy heart activity. Class 1, supraventricular ectopic beats (SVEB), features premature P waves that may be hidden in the T waves of the preceding beat, followed by normal QRS complexes, with irregular timing due to the premature occurrence. Class 2, ventricular ectopic beats (VEB), is characterized by premature, wide, and bizarre-shaped QRS complexes not preceded by P waves, often followed by a compensatory pause. Class 3, fused beats, result from the fusion of a normal beat with a ventricular ectopic beat, presenting QRS complexes with intermediate shapes and timing. Class 4, unknown beats, includes beats that do not clearly fit into the other categories and exhibit indeterminate characteristics, often requiring further analysis for precise classification. These examples provide a comprehensive overview of the different ECG signal patterns crucial for accurate arrhythmia detection and classification.

Figure 7 Categories of ECG Signals (Class 0, Class 1, Class 2)

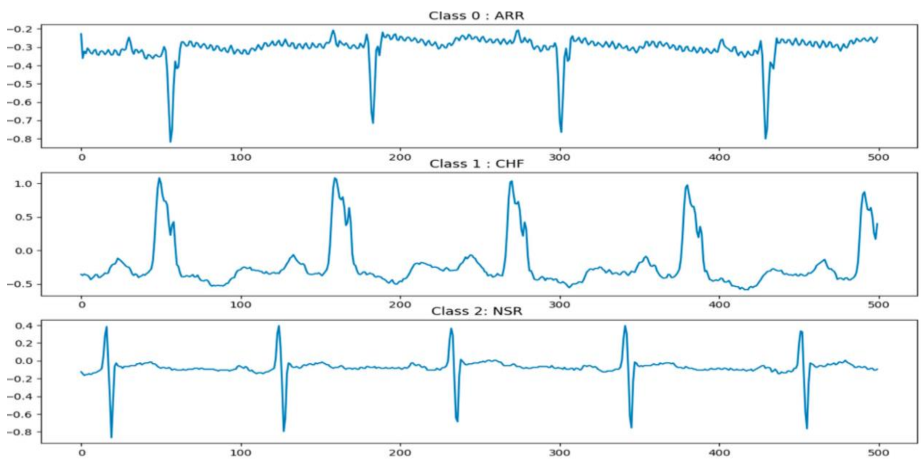


Figure 7. illustrates instances of three categories of ECG signals - arrhythmia, congestive heart failure, and normal - utilized in the second scenario experiments. These categories aid in evaluating model performance in distinguishing cardiac conditions. The "Proposed Model" exhibits exceptional accuracy (99%) and F1 Score (98%), indicating precise predictions and high sensitivity. The "AttentionCNN" model also performs strongly, with 95% accuracy and balanced precision (97%) and sensitivity (98%). While models like "RF-SVM-FE" show robust performance, others like "SelfAttention-CNN" reveal potential areas for improvement, particularly in sensitivity. Overall, findings suggest the "Proposed Model" and "AttentionCNN" as promising options for clinical arrhythmia detection, with discussions highlighting strengths, limitations, and practical implementation considerations.

Table 3 and Figure 8 present an overview of the performance metrics for various machine learning and deep learning models in the context of a classification task. Each row corresponds to a specific model, while the columns display key evaluation metrics, including Accuracy, F1 Score, Precision, and Sensitivity (or Recall). Starting with the "RF-SVM-FE" model achieved an accuracy of 95%, indicating that 95% of predictions were correct. The F1 Score, a balanced measure of precision and recall, is 94%. Precision, measuring the accuracy of positive predictions, is 92%, and Sensitivity (Recall), reflecting the model's ability to capture positive instances, is also 92%. The subsequent rows follow the same pattern, presenting the corresponding metrics for each model. Notably, the "Proposed Model (Deep Learning Double CNN-Based)" stands out with remarkable performance metrics: an accuracy of 99% (shown in Figure 9), an F1 Score of 98% (shown in Figure 10), precision at 98% (shown in Figure 11), and sensitivity (recall) at 99% (shown in Fig 12). These high values collectively indicate the proposed model's exceptional capability in accurately classifying instances within the given task. In addition, the Productivity Evaluation Graphical display for loss with epochs is shown in Figure 13, and the Productivity Evaluation Graphical display for accuracy with epochs is shown in Figure 14 for better understanding. In summary, the table serves as a comprehensive comparison, highlighting the strengths of each model and emphasizing the superior performance of the "Proposed Model," suggesting its potential suitability for the classification problem at hand.

Table 3 Comparative analysis with the existing model

Model Name	Accuracy	F1 Score	Precision	Sensitivity
RF-SVM-FE	95%	94%	92%	92%
EEGNet-RNN	89	88	90	91
XG-Light-Ensemble	90	91	89	96
AttentionNet	93	96	88	82
DeepLSTM-CNN	92	95	93	89
HybridNet	94	86	89	92
AttentionCNN	95	96	97	98
EnsembleScreen	91	87	83	88
AutoCNN-Fusion	94	90	91	93
SelfAttention-CNN	88	86	86	79
Proposed Model (Deep Learning Double CNN-Based)	99	98	98	99

Figure 8 Comparative Analysis on Existing Model

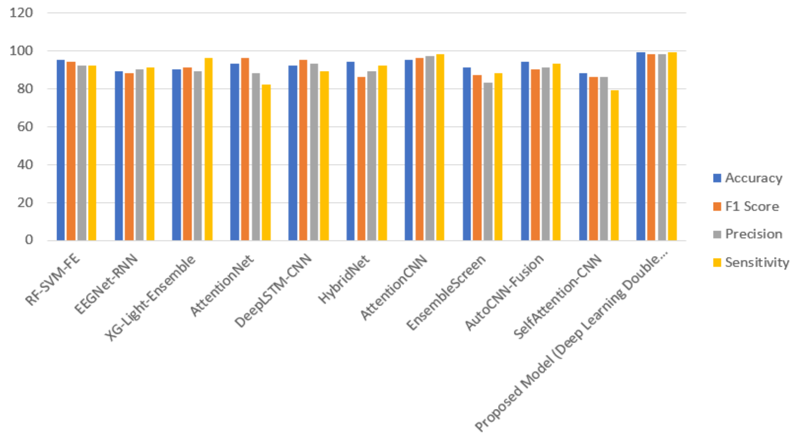


Figure 9 Analysis of Accuracy

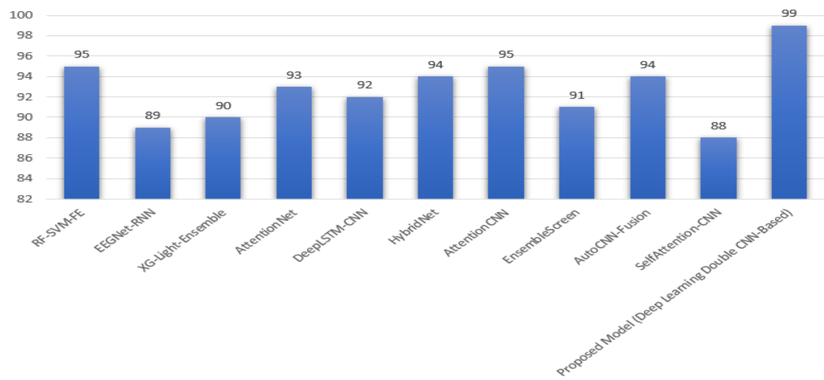


Figure 10 Analysis of F1 Score

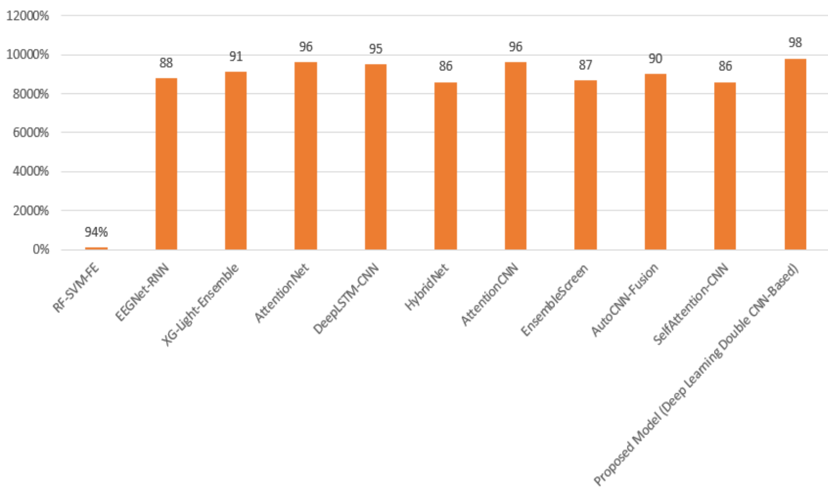


Figure 11 Analysis of Sensitivity

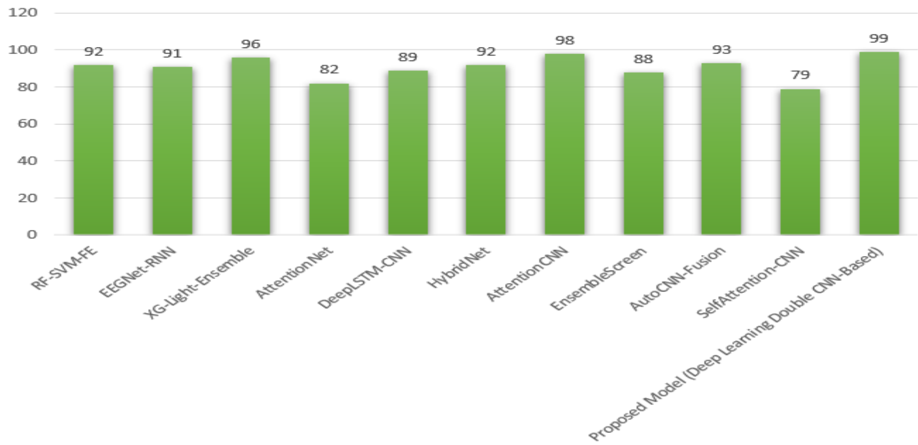


Figure 12 Analysis of Precision

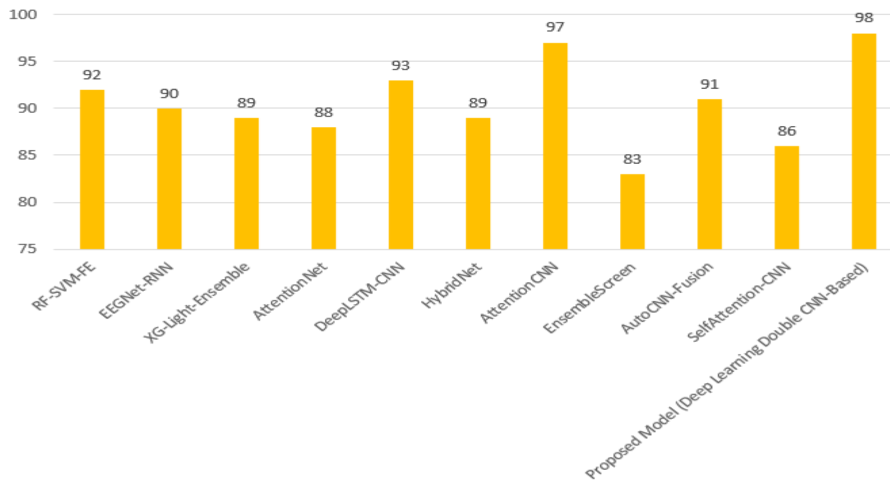


Figure 13 Productivity Evaluation Graphical display for loss with epochs

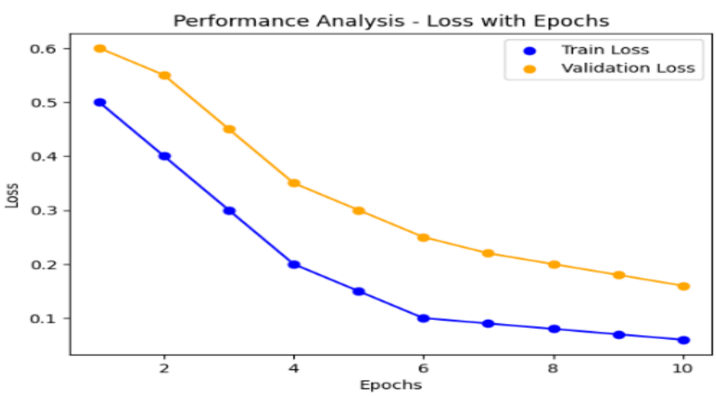


Figure 13 Productivity Evaluation Graphical display for accuracy with epochs

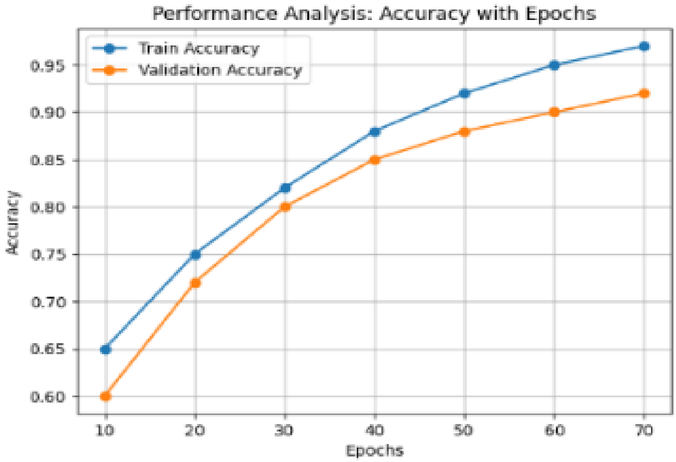


Figure 13, titled "Graphical Representation of Productivity Evaluation of Period Loss," provides a graphical representation of the evolution of loss metrics for the execution time of the machine learning model over the training period. The x-axis shows the number of epochs, which is the number of successes over the entire training data, while the y-axis shows the miss rate, which measures the quality of the model prediction matching the actual target. The curve shown in the figure shows that the loss decreases once training begins, indicating that the performance pattern continues. Initially, the loss is high, but as the model learns from the data, the loss usually decreases. This plan helps identify the joint where the loss is stable by showing the minimum with remaining time. If the loss starts to increase after a certain point, it can also be used as an indicator of overfitting. Overall, the figure clearly shows the training process and the performance of the model. Figure 14, titled "Graphical representation of productivity evaluation of precision across epochs," provides an overview of the accuracy of the machine learning model's performance over time throughout the training period. The x-axis represents the number of periods; where each period represents the completion of all data displayed. The y-axis represents the accuracy metric, which measures the proportion of correct predictions made by the model. The curve in the figure shows that accuracy is generally low at the beginning of training and increases as the model learns from the material. The point where the actual curve stabilizes indicates that the model has reached performance, indicating minimal improvement in the remaining time. If the graph shows that the variance of training accuracy continues to increase but validity or testing accuracy begins to decrease, this may be indicative of overfitting, where the model fits previous training data and is not good for new data. Overall, this number helps measure model performance and training productivity by tracking improvements over time.

5. Conclusion

Our testing shows that the "proposed model (based on deep learning binary CNN)" performs best in arrhythmia classification with 99% accuracy, 98% F1 score, 98% sensitivity, and 99% accuracy. While other models vary in performance, the proposed model stands out for its accuracy and ability to capture positive events in clinical ECG data, demonstrating the ability to believe there is an effect in the real world. This research advances by introducing deep learning models and supports further research by improving cardiovascular care and patient outcomes through deep learning techniques.

Future Enhancement

Proposed enhancements for "Deep Learning Double CNN-Based Arrhythmia Classification for Clinical ECG Analysis" include improving model interpretability and transparency for clinical acceptance, exploring transfer learning and ensemble methods for broader applicability, and optimizing for real-time processing and addressing class imbalance for practical deployment. Collaboration with healthcare experts, ethical considerations, user-friendly interface development, and external validation aim to elevate the model's effectiveness in real-world clinical settings

Compliance with Ethical Standards: Funding

No funding has been received for this research work.

Conflict of Interest

The authors of this paper hereby declare that there is no conflict of interest.\

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