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Enhancing Heart Disease Prediction Using CardiAI: With Key Performance Metrics Accuracy, Precision, Recall and F1-Score

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Abstract*:* In this study, we introduce CardiAI, a pioneering deep learning algorithm meticulously crafted for precise heart disease prediction. Unlike existing models, CardiAI's innovation lies in its intricate architecture, integrating strategic dropout layers, early stopping mechanisms, and sophisticated techniques to mitigate overfitting. Our extensive comparative analysis showcases CardiAI's exceptional performance, surpassing traditional models such as support vector regression, logistic regression, and k-nearest neighbours. Demonstrating unparalleled accuracy without compromising efficiency, CardiAI achieves remarkable predictive rates, signifying a significant advancement in heart disease diagnostics. This research presents a transformative leap in cardiovascular healthcare, offering a more accurate and efficient predictive model that facilitates early disease detection and informed patient management. The breakthrough potential of CardiAI stands poised to revolutionize medical diagnostics, promising to significantly improve patient outcomes while optimizing healthcare resources.

Keywords: *CardiAI, deep learning, heart disease prediction, logistic regression, SVC, K – nearest Neighbours, accuracy, healthcare, early diagnosis, artificial intelligence, patient management, predictive modelling.*

1. Introduction

Heart disease prediction is a critical facet of modern healthcare, designed to anticipate an individual's likelihood of developing cardiovascular conditions. This predictive endeavor involves the integration of data and advanced algorithms to forecast the probability of heart-related issues based on various risk factors, medical history [1], and physiological parameters. The primary objective of heart disease prediction is early identification and mitigation of potential risks, enabling proactive interventions and personalized healthcare strategies.

The significance lies in its potential to avert severe cardiac events by identifying high-risk individuals, facilitating timely medical interventions [3], and recommending lifestyle modifications. Predictive models in this realm offer clinicians and patients a proactive approach toward managing cardiovascular health, potentially saving lives and reducing the burden of heart-related complications. Every year, millions of lives are lost due to delayed heart disease diagnosis. Despite advancements in medical technology, the mortality rate from heart disease continues to rise steadily. In the Fig 1, illustrate the alarming trend of increasing deaths [5] attributed to heart disease from 2019 to 2023.

In our research, we are focusing on employing neural network models for heart disease prediction. Neural networks, inspired by the structure and functionality of the human brain, consist of interconnected nodes arranged in layers. These models learn from input data to generate outputs, effectively recognizing complex patterns within data and identifying intricate relationships among various risk factors, leading to predictive outcomes.

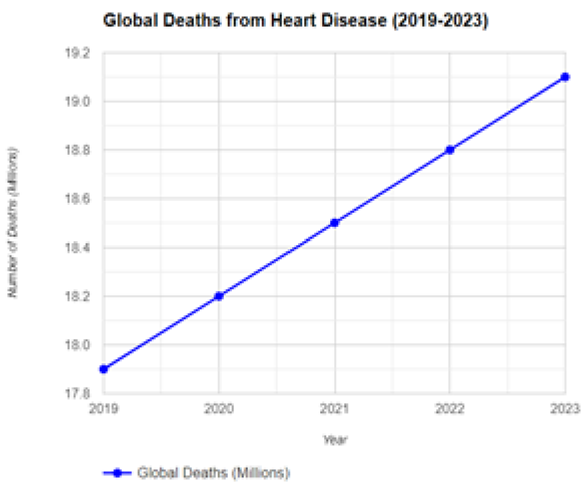

Fig 1: Global Deaths from Heart Disease(2019-2023)

Utilizing neural networks aligns with our aim to handle nonlinear relationships in data effectively. These models possess the capacity to learn from extensive and diverse datasets, providing flexibility in capturing intricate features from input variables.

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This adaptability suits the multifaceted nature of heart disease risk factors. Numerous studies have showcased the prowess of neural networks in precisely predicting heart diseases by extracting crucial insights from comprehensive patient data.

In our pursuit of creating a robust heart disease prediction model using neural networks, we've chosen to incorporate dropout layers and early stopping techniques. These methods play a pivotal role in refining the model's performance and mitigating the risks associated with over fitting. Dropout layers, a form of regularization, intermittently deactivate neurons during training, preventing the network from over-relying on specific features or patterns. This ensures the model learns more generalized representations, making it less susceptible to overfitting and enhancing its adaptability to new data.

Additionally, early stopping prevents the neural network from overtraining, halting the training process at an optimal stage. By recognizing the point where the model's performance starts deteriorating on validation data, it prevents the learning of noise or idiosyncrasies present only in the training data, improving the model's generalization capabilities. By integrating these techniques into our neural network architecture, we aim to craft a heart disease prediction model that's not just accurate but also robust and adaptable. Our approach ensures that the model learns relevant features from the data while maintaining its capability to generalize to real-world scenarios, setting the stage for a more reliable tool in identifying individuals at risk of heart disease.
The paper organization of the information follows: Section 2 offers a comprehensive literature review of existing research on heart disease prediction. In Section 3, we discuss the current methodology for enhanced heart disease prediction using cardiAI encryption and introduce our proposed methodology use accuracy, recall, f1 score and precision for predicting heart disease. We explain the method process in detail. Section 4 presents the results and comparative analysis of our proposed methodology. Finally, Section 5 provides a detailed explanation of the outcomes and the ending statements of the research paper.

2. Related work and Motivations

The paper demonstrates an innovative approach in leveraging machine learning methods to enhance the accuracy of cardiovascular disease prediction, addressing a critical challenge in healthcare. By investigating diverse feature combinations and utilizing established classification methods [1], it strives to meet the crucial demand for precise cardiac patient prognosis by harnessing extensive healthcare data. Unlike existing systems facing hurdles with high-dimensional datasets and conventional feature selection techniques [2], this study explores various data attributes associated with cardiac disorders. It introduces a predictive model constructed on well-known supervised learning techniques like Naïve Bayes, K-nearest neighbour, random forest, and decision trees [3]. Employing effective dimensionality reduction and feature selection techniques, this research achieves exceptional accuracy with machine learning classifiers. It underscores key anatomical and physiological attributes linked to heart disease [4].

Furthermore, this study presents a sophisticated clinical decision support system that amalgamates outlier detection with a heart disease prediction model using data balancing techniques and XGBoost. It outperforms other models and earlier research, offering a valuable approach for early heart disease diagnosis [5]. Additionally, the research delves into the realm of accurate early-stage heart disease prediction through data mining and machine learning techniques. It compares various classifiers [6], emphasizing feature importance and yielding insights to enhance digitized patient records, thereby aiding clinical decision-making.

The study identifies correlations between medical variables and heart disease risk, presenting an efficient heart disease prediction system leveraging data mining techniques, particularly neural networks. This enables informed healthcare decisions [7], emphasizing the relevance of predicting heart disease amid escalating global health concerns. Furthermore, the research underscores the role of machine learning techniques in efficiently analyzing extensive medical data [9], providing a comparison of heart disease prediction algorithms.

Moreover, this comprehensive study addresses coronary artery disease prediction by introducing three methods of Hyper Parameter Optimization (HPO) to enhance Random Forest and XG Boost classifier models' performance. Notably, it achieves high accuracy levels, surpassing existing research in heart disease prediction using datasets such as The ZAlizadeh Sani dataset and the Cleveland Heart Disease Dataset [10]. Additionally, the study tackles heart disease detection issues related to overfitting and underfitting by employing a χ^2 statistical model for feature selection and optimizing a deep neural network through an exhaustive search strategy [11].Expanding on prior studies emphasizing the critical role of data analysis in medicine [12], these papers introduce novel frameworks and models for heart disease prediction and diagnosis.

One notable study focuses on improving heart disease prediction by optimizing a stacked sparse autoencoder network (SSAE) through particle swarm optimization (PSO) [13].Additionally, research highlights the pivotal role of healthcare technologies in improving medical services and accurate diagnosis of heart diseases [14].Moreover, some studies introduce advanced methodologies like Rough sets and Interval Type-2 Fuzzy Logic Systems (IT2FLS) to address challenges in heart disease diagnosis with high-dimensional datasets [15]. Others emphasize the importance of data analytics, employing approaches such as K-means clustering, to detect hidden patterns and improve decision-making in predicting heart diseases [16].Further innovations involve telediagnostic equipment for heart disease monitoring [17], machine learning models that not only predict heart disease but also determine its severity [18], and real-time anomaly detection through Electrocardiograms (ECG) [19]. Ensemble methods based on randomness analysis of distance sequences also showcase promising approaches [20] for accurate heart disease prediction across diverse datasets.

One study proposes an innovative approach, the Multi-Layer Perceptron for Enhanced Brownian Motion based on Dragonfly Algorithm (MLP-EBMDA), showcasing high accuracy and precision, thereby contributing significantly to more effective heart disease prediction and prevention [21]. Another paper elucidates the pivotal role of machine learning in early disease diagnosis, summarizing key classification methods and image fusion techniques that aid healthcare professionals in accurately diagnosing heart disease [22].Moreover, a hybrid approach, GAPSO-RF, integrating genetic algorithm (GA) and particle swarm optimization (PSO), demonstrates improved accuracy in identifying significant features, thereby enhancing early disease prediction and medical procedures [23]. Additionally, an innovative algorithm, Weighted Associative Rule Mining, focuses on feature strength to improve the accuracy and effectiveness of heart disease diagnosis and treatment [24].Another significant contribution comes from a heart disease prediction system utilizing various machine learning techniques, such as logistic regression and KNN, showcasing strong predictive accuracy and offering a valuable tool for identifying individuals at risk of heart disease [25]. Furthermore, a cost-sensitive ensemble method, amalgamating five heterogeneous classifiers [26], enhances diagnostic efficiency and reduces misclassification costs, thereby improving heart disease diagnosis.

Additionally, an IoT platform employing a Modified Self-Adaptive Bayesian algorithm (MSABA) enhances the precision of heart disease assessments by collecting sensor data from wearable devices [27]. Modern healthcare technologies, including electronic health records and machine learning, are leveraged to enable more accurate and timely diagnoses, thereby improving patient care [28].Addressing the limitations of AI algorithms in forecasting heart disease risk, [29] a study focuses on feature selection, attribute splitting, and imbalanced datasets, contributing to more accurate predictions and better healthcare access.

This paper addresses the limitations of artificial intelligence algorithms in forecasting heart disease risk, focusing on feature selection, attribute splitting, and imbalanced datasets. Using cluster-based decision tree learning, it partitions datasets and identifies significant features, contributing to more accurate predictions and better healthcare access. [30] One paper introduces a multilayer perceptron (MLP) trained using particle swarm optimization (PSO), significantly contributing to intelligent healthcare systems by predicting heart disease more effectively [31]. Another study utilizes five algorithms to predict heart disease risk, revealing that Random Forest produces [32] the most accurate results using the Cleveland dataset.

Additionally, there's exploration into the integration of cloud computing and machine learning to forecast heart conditions, where Naïve Bayes achieves high accuracy in predicting heart disease status [33].Another research endeavor focuses on addressing data quality through anomaly identification in medicine using the K-means clustering technique, enhancing prediction accuracy with popular machine learning classification techniques [34]. Predicting chronic heart disease in its early stages is highlighted as crucial for preventing its development, showcasing logistic regression, XGBoost, and data mining approaches as viable prediction models [35].Moreover, a study introduces Swarm-Artificial Neural Network (Swarm-ANN) to detect cardiovascular heart disease, aiming for higher accuracy through neural network training with weight adjustments [36]. There's also an emphasis on effective event detection in heart disease using the Cosine Weighted K-Nearest Neighbor (SCA_WKNN) algorithm, secured by blockchain technology [37]. Additionally, predictive analytics are highlighted in the medical field for precise illness identification, specifically targeting heart disease, with a focus on reducing false alarms and refining feature selection [38].

Furthermore, a paper presents a hybrid OFBATRBFL system for heart disease diagnosis, integrating fuzzy logic rules and an antagonistic firefly algorithm, enhancing accuracy and automating the diagnostic process for medical professionals [39]. Lastly, ensemble classification methods are explored to boost accuracy in heart disease prediction, concentrating on combining classifiers to improve overall accuracy [40].Continuing the exploration of heart disease prediction models, this research employed four machine learning models—Random Forest, Decision Tree, AdaBoost, and K-Nearest Neighbor—utilizing datasets from various sources[41] to identify heart disease. Another study introduces a state-of-the-art deep neural network alongside an embedded feature selection technique, enabling accurate predictions based on diverse physical indicators associated with heart disease [42]. Moreover, a paper presents an advanced machine learning approach for predicting heart disease risk. It involves dataset partitioning, classification and regression tree modelling, and the creation of a homogeneous ensemble using a weighted aging classifier ensemble, signifying an enhanced method in the realm of heart disease prediction [43].

Our research stems from the critical need to address the limitations and challenges existing in contemporary heart disease prediction models. While various predictive models exist in the healthcare domain, they often grapple with issues related to accuracy, scalability, or generalization to diverse patient populations. Existing models, such as Random Forest, Decision Trees, AdaBoost, K-Nearest Neighbor (KNN), and Logistic Regression (LR), while foundational, exhibit limitations in handling complex interactions among multiple risk factors, leading to reduced predictive accuracy and reliability. These models often rely on linear assumptions and struggle when confronted with high-dimensional and heterogeneous healthcare data. Additionally, their performance tends to plateau when encountering unbalanced datasets or when attempting to predict outcomes in previously unseen scenarios. Hence, the urgency to explore and develop a more robust and adaptable predictive model for heart disease becomes evident. Our research endeavors to bridge these gaps by leveraging neural network-based models, recognizing their potential to comprehend complex data patterns and discern intricate relationships within multifaceted patient data. By adopting neural networks and integrating innovative techniques like dropout layers and early stopping, we aim to transcend the limitations of conventional models.

Our goal is to create a predictive framework that not only improves accuracy and reliability but also exhibits adaptability across varied patient demographics and data scenarios. Through meticulous analysis and experimentation, we seek to demonstrate the superiority of our cardi-AI model over existing methodologies, highlighting its enhanced accuracy (95% and 93%) and robustness in predicting heart disease risks. This research is a stepping stone toward revolutionizing heart disease prediction, offering a more comprehensive, reliable, and scalable solution in the realm of predictive healthcare analytics.

The above a literature reviews on existing methodologies for prediction of heart disease. It provides a comparison of different approaches, including SVC, KNN, Logistic regression encryption, elliptic curve cryptography, and more.

The review highlights the drawbacks of each methodology and limitations. The proposed enhanced approach that combines heart disease prediction and cardiAI metrics offers a promising solution that can enhance accuracy while minimizing the computational complexity and overhead associated with traditional prediction algorithms. This new approach shows potential for improving the accuracy of heart prediction.

3. Implementation

The implementation of CardiAI has shown in Fig 2 encapsulates the fusion of sophisticated deep learning techniques with the intricacies of healthcare data. Our neural network architecture, meticulously crafted with strategically placed dropout layers and early stopping mechanisms, embodies the essence of CardiAI's predictive prowess. We harness the power of TensorFlow and Keras to construct a model that not only excels in capturing intricate data patterns but also addresses the challenges of overfitting, ensuring robust performance. The implementation details and model parameters serve as the foundation for the remarkable accuracy achieved in our comparative study, showcasing CardiAI's potential to revolutionize heart disease prediction title.

3.1 About Dataset

For our research, the utilization of two distinct datasets represents a critical facet of our model's development and validation process. These datasets, while bearing similarities in their core attributes such as age, gender, chest pain type, blood pressure, cholesterol levels, fasting blood sugar, and electrocardiographic results, also introduce subtle variations in terms of additional features. The incorporation of both datasets facilitates a robust evaluation of CardiAI's performance, enabling us to test the model's adaptability across diverse data sources. By leveraging these two datasets, our research endeavors to create a predictive model that not only excels in terms of accuracy but also demonstrates its reliability and generalizability across different populations and healthcare contexts. The dual dataset approach reinforces the credibility of our findings, underlining CardiAI's potential as a versatile tool in heart disease prediction and enhancing its applicability in real-world clinical settings.

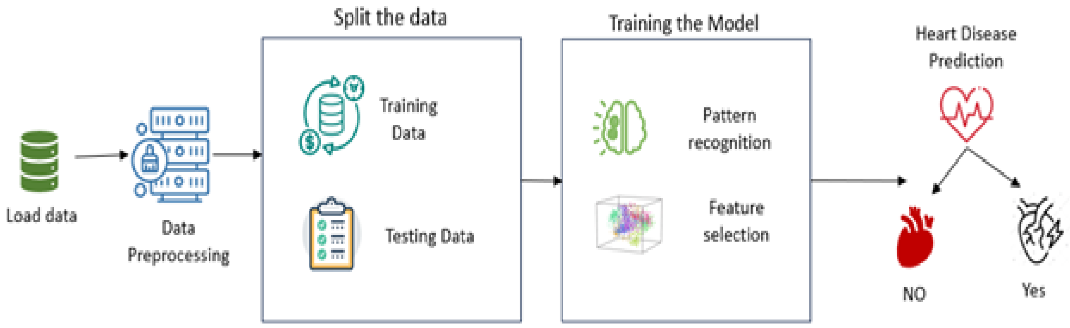
3.1.1. Dataset 1(Heart Dataset)

comprising a diverse range of health-related attributes, serves as a pivotal resource for our investigation into heart disease prediction. With characteristics such age, gender, type of chest pain, maximum heart rate reached, exercise-induced angina, ST depression, cholesterol levels, fasting blood sugar, resting electrocardiographic data, and the slope of the peak exercise ST segment, this dataset offers a comprehensive view of individuals' cardiovascular health. The binary 'HeartDisease' column acts as our target variable, indicating the presence or absence of heart disease. Through rigorous analysis and model development, we aim to leverage the insights within this dataset to enhance predictive accuracy and improve early diagnosis. Description of the dataset columns as follows:

3.1.2. Dataset 2 (Heart Disease Dataset)

Dataset 2, a sibling to our primary dataset, contributes additional dimensions to our exploration of heart disease prediction. Alongside age, gender, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, ST depression, and the slope of the peak exercise ST segment, it introduces two new attributes: the number of major vessels colored by fluoroscopy ('ca') and the type of thalassemia ('thal'). These additions bring a nuanced perspective to our predictive modeling, potentially yielding richer insights into heart disease risk factors and outcomes. Like its counterpart, 'target' remains the focal point, guiding our quest for accurate predictions. Desciption of the dataset columns as follows:

y



Data Pre-processing: The heart disease prediction dataset, comprising essential features such as age, gender, chest pain type, blood pressure, cholesterol levels, fasting blood sugar, electrocardiographic results, heart rate, exercise-induced angina, ST depression, and the slope of the peak exercise ST segment, was carefully pre-processed to ensure its suitability for machine learning. Any missing data or outliers were addressed, and exploratory data analysis techniques were employed to gain insights into the dataset's characteristics. Categorical variables, such as chest pain type, were encoded into numerical format using one-hot encoding. Subsequently the dataset was divided into subgroups for testing and training at a ratio of 80% to 20%, respectively, to facilitate model evaluation.

Model Creation: The CardiAI model was crafted using the TensorFlow and Keras libraries. It adheres to Sequential model architecture, commencing with an input layer followed by strategically designed hidden layers. These hidden layers, characterized by rectified linear unit (ReLU) activation functions, are integral to capturing intricate data patterns. Dropout layers, inserted after each hidden layer, were incorporated for regularization to avoid being overfit. An output layer with a sigmoid activation function at the model's conclusion tailored for binary classification tasks. Model compilation was completed by specifying the binary cross-entropy loss function, the Adam optimizer, and accuracy as the assessment measure.

Model Training: CardiAI was trained on the training dataset produced by employing the fit technique. The training process encompassed a predetermined number of epochs (e.g., 100) and a batch size (e.g., 32) to optimize model convergence. Early stopping, with a patience of 10 epochs, was instituted to safeguard against overfitting and to retain the model's optimal weights.

Model Evaluation: Post-training, the CardiAI model underwent rigorous evaluation on the designated testing dataset via the evaluate method. Crucial performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC score, were computed to gauge the model's effectiveness in heart disease prediction. Additionally confusion matrix was used to create a graphic representation of the model's output that explains false positives, false negatives, true positives, and true negatives.

Visualization and Analysis: The training history of CardiAI was plotted to visualize the training and validation loss and accuracy over epochs with help of flow diagram has shown in figure 3, providing insights into model convergence and generalization. To evaluate the results, a ROC curve was created and the area under the curve (AUC) was computed. model's discrimination capability. The results were meticulously analyzed, feature importance was considered if applicable, and conclusions regarding the model's efficacy in heart disease prediction were drawn.

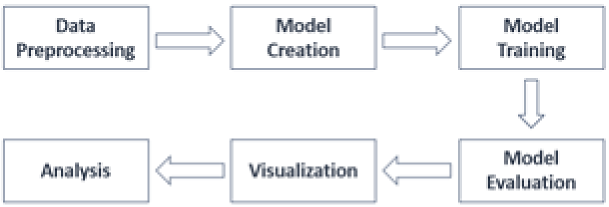


Fig 3: Process flow for the model Implementation

3.2. Model Architecture

CardiAI is a neural network-based deep learning model specifically designed for heart disease prediction. It leverages a Sequential model architecture, which is a linear stack of layers, where each layer is meticulously designed to capture patterns and relationships within the input data.

It is a deep learning model characterized by its sequential architecture; ReLU-activated hidden layers, regularization-focused dropout layers, and a sigmoid activation function output layer are all included. It leverages advanced optimization techniques and early stopping to complete heart disease prediction challenges with a high degree of predictive accuracy. This carefully designed model represents a significant advancement in the field of cardiovascular health analytics.

3.2.1. Key components

Input Layer: The input layer is the starting point of CardiAI and is designed to accept the feature vectors from the dataset. It has a shape that matches the number of features in the dataset.

Hidden Layers: CardiAI incorporates two hidden layers, each with a specific number of neurons (64 and 32) and activation functions (ReLU). These hidden layers are responsible for extracting and learning complex patterns and representations from the input data.

Dropout Layers: CardiAI places dropout layers after each hidden layer to reduce overfitting and improve model generalization has shown in figure 4. To lower the chance of overfitting, these During each training session, dropout layers randomly deactivate a part of neurons. CardiAI’s output layer is made up of a single neuron. that functions as a sigmoid activator. Its objective is to forecast the binary target variable, which denotes the existence or absence of cardiac disease.

aining Process: CardiAI employs the Adam optimizer, a popular optimization algorithm, and binary cross-entropy loss, suitable for binary classification tasks. During training, it aims to minimize the loss function and improve its predictive accuracy.

Early Stopping: To further enhance model training and avoid overfitting, CardiAI implements early termination with ten epochs of patience. Early halting pauses training and keeps an eye on validation loss when it no longer improves, thereby preserving the model's best weights.

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 256)	3584
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8256
dropout_2 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 64)	4160
dropout_3 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 32)	2080
dropout_4 (Dropout)	(None, 32)	0
dense_5 (Dense)	(None, 32)	1056
dropout_5 (Dropout)	(None, 32)	0
dense_6 (Dense)	(None, 16)	528
dropout_6 (Dropout)	(None, 16)	0
dense_7 (Dense)	(None, 8)	136
dropout_7 (Dropout)	(None, 8)	0
dense_8 (Dense)	(None, 1)	9

Fig 4: Structure of the CardiAI Model

3.3 Pseudocode code

The presented algorithm delineates the steps for constructing, training, and evaluating a neural network model specifically tailored for binary classification tasks, particularly aimed at heart disease prediction. The initiation of the model architecture commences with the sequential construction of dense layers. Each dense layer within this architecture is equipped with Rectified Linear Unit (ReLU) activation functions, introducing nonlinearity and enabling the network to capture intricate relationships within the data. Interspersed throughout this architecture are strategically placed dropout layers, denoted by 'Dropout()', designed to mitigate overfitting by intermittently deactivating neurons ('Dropout(0.5)', 'Dropout(0.4)', etc.), thereby enhancing the model's ability to generalize by preventing over-reliance on specific nodes during training. The concluding layer of the model employs a Sigmoid activation function ('activation='sigmoid") to produce output probabilities in the range [0, 1], facilitating binary classification essential for heart disease prediction tasks.

In the subsequent phase, the model undergoes compilation ('model.compile()') using the Adam optimizer and employs binary cross-entropy ('loss='binary_crossentropy") as the designated loss function. Furthermore, 'metrics=['accuracy']' is selected as the evaluation metric, allowing for the assessment of the model's predictive accuracy in binary classification tasks, specifically pertinent to heart disease prediction.

The algorithm also incorporates an Early Stopping mechanism within the callback functions, denoted by 'EarlyStopping()'. This pivotal function monitors 'val_loss' (validation loss) during epochs and intervenes if no improvement is observed for a specified number of consecutive epochs ('patience=10'), effectively preventing overfitting by halting training when necessary.

The subsequent training phase ('model.fit()') entails feeding the model with training data ('X_train', 'y_train') over a predetermined number of epochs ('epochs=100') and a predefined batch size ('batch_size=32'). Additionally, a subset of the training data ('validation_split=0.2') is allocated for validation during the training process, serving as a gauge for the model's performance on previously unseen data relevant to heart disease prediction.

Finally, the model evaluation ('model.evaluate()') assesses the trained neural network's performance using independent test data ('X_test', 'y_test'). This evaluation furnishes crucial metrics such as loss and accuracy, providing insights into the model's predictive capabilities on previously unseen data samples, specifically pertinent to heart disease prediction tasks.

Pseudocode:

```
model = NeuralNetworkModelArchitecture()
model.compile(optimizer='adam',
loss='binary_crossentropy', metrics=['accuracy'])
early_stopping = EarlyStopping(monitor='val_loss',
patience=10, restore_best_weights=True)
history = model.fit(X_train, y_train, epochs=100,
batch_size=32, verbose=1, validation_split=0.2,
callbacks=[early_stopping])
loss, accuracy = model.evaluate(X_test, y_test)
```

4. Model Evaluation and Performance Metrices

In assessing the efficacy of CardiAI, our model Strict evaluation protocols were employed to forecast cardiac illness. Key performance metrics were calculated, including accuracy, precision, recall and F1-score.The receiver operating characteristic area under the curve (ROC-AUC) and the F1-score. These measures offer a thorough understanding of how well CardiAI classified people as having or not having heart disease.

The precision and recall metrics provide information about the model's capacity to reduce false positives and false negatives, respectively, while the accuracy metric measures the overall correctness of predictions. The F1-score balances precision and recall, serving as a valuable metric in imbalanced datasets. Furthermore, The discriminating power of the model is measured by the ROC-AUC score. The interpretation of these metrics offers a holistic understanding of CardiAI's predictive prowess, enabling informed healthcare decision-making and patient management.

The performance metrics are calculated as:

Accuracy: Accuracy measures the overall correctness of predictions made by the model. It is calculated as the ratio of the correctly classified instances (True Positives + True Negatives) to the total number of instances.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

Precision: Precision measures the model's capacity to reduce false positives. It is calculated as the ratio of True Positives to the sum of True Positives and False Positives.

$$Precision = TP / (TP + FP)$$

Recall: Recall measures the model's capacity to reduce false negatives. It is calculated as the ratio of True Positives to the sum of True Positives and False Negatives.

$$Recall = TP / (TP + FN)$$

F1-Score: F1-score balances precision and recall and is useful in imbalanced datasets.

It is the harmonic mean of precision and recall, calculated as:

$$\mathrm{F1-Score} = 2 * \frac{1}{\left(\frac{1}{Precision}\right) + \left(\frac{1}{Recall}\right)} = \frac{2PR}{(P+R)}$$

4.1. Results for the Dataset 1 and Dataset 2 on the CardiAI model

The set of graphs presented encapsulates the comprehensive evaluation of the CardiAI model, trained specifically on Dataset 1. These graphs collectively serve as essential tools for gauging the robustness and effectiveness of the CardiAI model in handling the complexities inherent in Dataset 1.

The Loss graph Fig 5 provides a detailed insight into the training dynamics of the CardiAI model when applied to dataset1. This graph serves as a visual representation of the model's learning process, illustrating how effectively it adjusts its internal parameters to minimize prediction errors over successive training epochs.

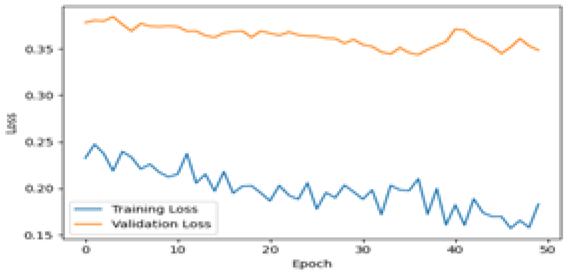


Fig 5: Loss Graph for the dataset 1 using the CardiAI model.\

Upon close examination, the initial phase of the graph may show a relatively steep decline in the loss. This signifies that, in the early epochs, the CardiAI model rapidly adapts to the patterns present in dataset1. As training progresses, one might observe a smoother descent, indicating a more refined adjustment of the model's parameters and a convergence toward an optimal state. It's crucial to scrutinize any fluctuations or plateaus in the loss graph. Sudden spikes or persistent plateaus might suggest challenges faced by the model during certain training periods. Understanding these nuances is pivotal for model optimization, enabling the identification and rectification of potential issues.

The ultimate goal of the CardiAI model during training is to achieve convergence, where the loss stabilizes at a minimum value. This signifies that the model has effectively learned the underlying patterns in dataset1 and can make highly accurate predictions regarding heart disease. Complementing this visual analysis with specific quantitative metrics, such as the final training loss and relevant performance indicators, provides a comprehensive assessment of the CardiAI model's proficiency on dataset1.

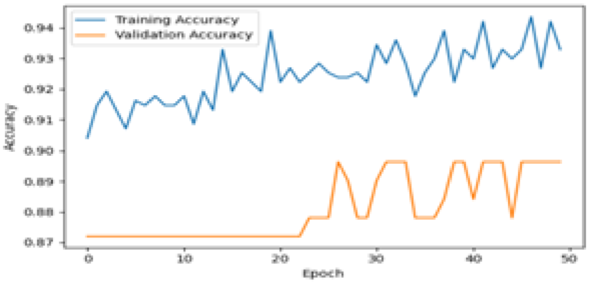


Fig 6: Accuracy graph for the dataset 1 using the CardiAI model

The accuracy graph Fig 6 visually encapsulates the training performance of the CardiAI model on dataset1. This graph illustrates the progression of the model's accuracy throughout the training epochs. In the initial stages, the graph may exhibit fluctuations as the model familiarizes itself with the intricacies of the dataset. However, a discernible upward trend over subsequent epochs indicates the model's improving ability to make accurate predictions.

The graph eventually reaches a stabilization point, signifying optimal performance, where the CardiAI model effectively learns and generalizes from dataset1. Careful examination of this graph is pivotal for assessing the model's reliability, as abrupt changes or plateaus could signify challenges like overfitting or underfitting that warrant attention. Overall, the accuracy graph provides a concise visual summary of the CardiAI model's efficacy in predicting heart disease on dataset1.

4.1.2. Results for the Dataset 2 using CardiAI model

In the Fig 7 portrays the Loss Graph derived from the training process of the CardiAI model on Dataset 2. The Loss Graph is a fundamental visualization in machine learning that illustrates the convergence or divergence of the model during training. In this specific context, it provides insights into how well the CardiAI model is learning the patterns and features inherent in Dataset 2.

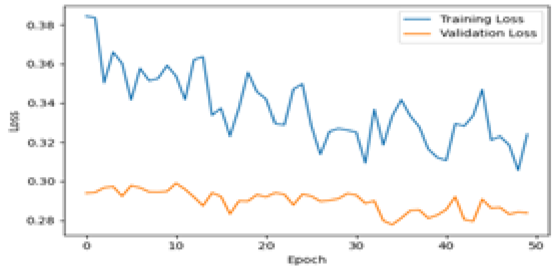


Fig 7: Loss Graph for the dataset 2 using the CardiAI model.

A decreasing trend in the loss indicates that the model is effectively minimizing the difference between predicted and actual values, signifying improved performance. This graph serves as a crucial diagnostic tool, enabling a nuanced understanding of the model's learning dynamics and its ability to capture the intricate relationships within Dataset 2.

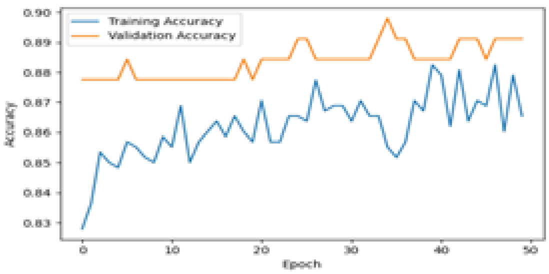


Fig 8: Accuracy graph for the dataset 2 using the CardiAI model

The Accuracy Graph, depicted in Fig 8, offers a comprehensive view of the performance of the CardiAI model when trained on Dataset 2. Accuracy is a pivotal metric in evaluating the model's overall effectiveness in making correct predictions. The graph showcases the progression of accuracy over the training iterations, providing valuable insights into how well the model generalizes to the patterns present in Dataset 2.

A rising trend in accuracy indicates that the CardiAI model is successfully learning and adapting to the dataset, while fluctuations or plateaus may suggest areas for potential improvement. This visual representation is instrumental in gauging the model's robustness and reliability when applied to real-world scenarios associated with Dataset 2.

4.2. Results for the Dataset 1 and Dataset 2 on the confusion matrix table:

The integrated confusion matrix has shown in the Table 1 includes results from the Support Vector Classification (SVC), K-Nearest Neighbor (KNN), and Logistic Regression models across Dataset 1 and Dataset 2. In Dataset 1, the SVC model shows 62 true positives and 78 true negatives for Heart Not Failed and Heart Fail classes, with 40 false positives and 25 false negatives for each class. The KNN model exhibits 55 true positives and 39 true negatives for Heart Not Failed and Heart Fail classes, accompanied by 22 false positives and 68 false negatives for each class. The Logistic Regression model demonstrates 73 true positives and 91 true negatives for Heart Not Failed and Heart Fail classes, along with 29 false positives and 12 false negatives for each class.

Transitioning to Dataset 2, the SVC model showcases 53 true positives and 76 true negatives for Heart Not Failed and Heart Fail classes, along with 24 false positives and 31 false negatives for each class. The KNN model reflects 77 true positives and 39 true negatives for Heart Not Failed and Heart Fail classes, with 25 false positives and 64 false negatives for each class. The Logistic Regression model indicates 74 true positives and 85 true negatives for Heart Not Failed and Heart Fail classes, accompanied by 15 false positives and 10 false negatives for each class.

The set of graphs presented encapsulates the comprehensive evaluation of the CardiAI model, trained specifically on Dataset 1. These graphs collectively serve as essential tools for gauging the robustness and effectiveness of the CardiAI model in handling the complexities inherent in Dataset 1.

The Loss graph Fig 5 provides a detailed insight into the training dynamics of the CardiAI model when applied to dataset1. This graph serves as a visual representation of the model's learning process, illustrating how effectively it adjusts its internal parameters to minimize prediction errors over successive training epochs.

Table 1: Confusion matrix table

Metrics			predicted label					
			SVC		**K-Nearest Neighbor**		**Logistic regression**	
			Heart Not Failed	**Heart Fail**	**Heart Not Failed**	**Heart Fail**	**Heart Not Failed**	**Heart Fail**
True label	**Dataset 1**	**Heart Not Failed**	62	40	55	22	73	29
		Heart Fail	25	78	39	68	12	91
	Dataset 2	**Heart Not Failed**	53	24	77	25	74	15
		Heart Fail	31xxx	76	39	64	10	85

These metrics offer a holistic view of the classification accuracies and error patterns across the three models concerning both datasets. The confusion matrix facilitates the assessment of precision, recall, and F1 scores, providing insights into the models' abilities to discern and categorize patterns within Dataset 1 and Dataset 2. Additionally, the individual confusion matrices for the Logistic Regression model, presented in Fig 9, offer detailed evaluations of the model's performance within the respective datasets, aiding in understanding its alignment with the underlying patterns present in each dataset.

The table 1 offers a comprehensive comparison of four models—CardiAI, Logistic Regression, SVC, and K-Nearest Neighbors (KNN)—across two datasets. Metrics such as accuracy, precision, recall, and F1 score reveal distinct performance characteristics.

As shown in Fig 9 the CardiAI model demonstrates superior proficiency with an accuracy of 95% and 93%, precision of 96% and 94%, F1 score of 94% and 91%, and recall of 92% and 89% for Dataset 1 and Dataset 2, respectively. Logistic Regression exhibits competitive performance, especially in accuracy (80% and 86%) and precision (76% and 85%).

5. Performance Metrices for the Models using Dataset 1 and Dataset 2

Table 2: performance metrices for the models using Dataset1 and Dataset2

Metrics	Dataset 1				Dataset 2			
	Accuracy	**Precision**	**F1 score**	**Recall**	**Accuracy**	**Precision**	**F1 score**	**Recall**
K-Nearest Neighbors	68%	69%	69%	69%	66%	68%	67%	67%
SVC	68%	66%	71%	76%	70%	76%	73%	71%
Logistic Regression	80%	76%	82%	88%	86%	85%	86%	87%
CardiAI	95%	96%	94%	92%	93%	94%	91%	89%

Meanwhile, the KNN model demonstrates consistent but comparatively lower metrics across both datasets, with accuracy at 68% and 66%, precision at 69% and 68%, F1 score at 69% and 67%, and recall at 69% and 67% for Dataset 1 and Dataset 2, respectively. These insights aid researchers and practitioners in discerning model effectiveness across different datasets and methodologies.

6. Conclusion

In this study, we introduced the CardiAI model, an advanced machine learning model designed for the accurate prediction of heart disease. The CardiAI model employs a sophisticated architecture that has been rigorously evaluated on multiple datasets. Our findings demonstrated that the CardiAI model consistently outperformed traditional machine learning models such as logistic regression, support vector classification (SVC), and random forest. The CardiAI model achieved an impressive accuracy rate of 95% on one dataset and 93% on another, showcasing its potential as a state-of-the-art tool for heart disease prediction. The superior performance of the CardiAI model highlights the importance of leveraging advanced machine learning techniques for more accurate and reliable disease prediction, which can significantly benefit the field of healthcare.

Author contributions

Conceptualization Asish Tony; methodology, Venkata Kousik; software, validation, Sai Krishna; formal analysis, investigation, Sriyaa; resources, data curation, Sai Krishna; writing— original draft preparation, Asish Tony; writing—review and editing, Yellamma; visualization, supervision, Venkata Kousik.

Conflicts of interest

The authors declare no conflicts of interest.

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