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Research Article

Transformative AI Solutions: A Hybrid Diagnostic Model for Cardiovascular Disease Utilizing Comprehensive Feature Analysis

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ABSTRACT

CVD is the number one disease that causes death around the globe, making it crucial to develop early and precise prediction models which can help in prevention. In this paper, we propose a hybrid deep learning model with CNN and Multilayer Perceptron (MLP) Neural Networks for CVD classification. The model aims to improve the predictive performance of CVD by using important patient health metrics like blood pressure, cholesterol level, BMI, and lifestyle choices. Utilizing CNN deep learning techniques on Processed Medical Data allows us to extract sophisticated features and patterns. Simultaneously, MLP integrates complex feature interaction which further enhances classification performance. Proposed system is evaluated with accuracy, precision, recall, f1 score and area under curve of Receiver Operating Characteristics (AUC-ROC) to achieve results in standalone models. Results showed that the hybrid CNN- MLP model outperforms the fundamental models and achieves the set benchmarks. These results imply the utility of the CNN- MLP hybrid model as a powerful, easy-to-use, and efficient CVD decision-support system for early AI diagnosis. This work assists in personalized medicine, telehealth and urgent healthcare service delivery to advance the use of AI technologies for automation of medical diagnostics.

Keywords: Cardiovascular Disease, Machine Learning, Convolutional Neural Network, Multi-Layer Perceptron, Early Detection, Healthcare AI.

INTRODUCTION

Globally, cardiovascular diseases (CVDs) are still the primary cause of death, contributing to approximately 31% of all deaths each year. The growing prevalence of CVDs has placed a substantial burden on healthcare systems worldwide, affecting both expenses and patient results (Mohan et al., 2019; Sudha & Kumar, 2023). While early detection and prompt treatment are vital for reducing serious complications, conventional diagnostic methods like electrocardiograms (ECGs), echocardiography, angiography, and blood tests often have drawbacks, including being invasive, expensive, and requiring specialized expertise (Almulihi et al., 2022; Jain et al., 2023; Mehul Mahrishi et al., 2020). To overcome these limitations, the incorporation of sophisticated artificial intelligence (AI) and machine learning (ML) methodologies is essential for creating diagnostic systems that are non-invasive, efficient, and precise (Golande & Pavankumar, 2023; Mohammad & Al-Ahmadi, 2023).

Results from recent studies concerning cardiovascular disease prediction with machine learning have shown great promise in boosting the accuracy of diagnosis (Shankar et al., 2020). However, many classical methods of ML such as Random Forest, Gradient Boosting, and even Decision Trees, have problems with high dimensional data due to overfitting, inefficient feature selection, or data modeling which negatively influences prediction accuracy. To address these constraints, some researchers have worked using combinations of hybrid models that integrate multiple Deep Learning (DL) algorithms (Mahmud et al., 2023). These hybrid models achieved remarkable results in feature extraction and classification processes, especially models with Convolutional Neural Network (CNN) components and Multi-Layer Perceptron (MLP) (Mijwil et al., 2022; Sudha & Kumar, 2023). CNNs are well-known for their performance in capturing spatial and intricate pattern variability in both structured and unstructured medical data, while MLP (Rustam et al., 2022), a deep feedforward neural network, specializes in non-linear representation learning along with relationships among features. The combination of these models helps improve accuracy, recall, and specificity for CVD detection.

For the classification of cardiovascular diseases, we designed an integrated deep learning framework combining CNN and MLP architectures. Utilizing primary health indicators like blood pressure (BP), cholesterol level (CL), body mass index (BMI), and other relevant lifestyle choices, the model strives for accurate predictions. CNN is utilized to perform feature extraction which involves complex interplay within the data and MLP captures the classification node to separate the two classes of data; patterns associated with healthy individuals and those who are at risk. Moreover, to improve predictive power, weighted averaging and hyperparameter tuning were employed as additional steps in predictive performance optimization. Classification based evaluation is done through standard and widely accepted metrics such as: accuracy, precision, recall, F1-score, and AUC-ROC score, so as to confirm the model's efficacy through multi-faceted assessment (Durairaj M & Revathi V, 2015; Youssef et al., 2025).

The advantages of the AI-driven CVD prediction system are scalability, health monitoring adaptability in real-time, and flexibility. The amalgamation of CNN and MLP creates a decision-support (Gupta et al., 2022; Mahmud et al., 2023; Ramasamy et al., 2021) system that works accurately and effectively and helps the other healthcare staff in making early diagnosis, treatment customization, and risk analysis. This research is part of the developing digital medicine, remote healthcare, and artificial intelligence medicine research focusing on advanced AI applications concerning cardiovascular disease management (Almulihi et al., 2022; Patel et al., 2022). This paper proceeds as follows: Section 3 describes the methodology and proposed dataset, Section 4 discusses the evaluation performed and analyzed the experiment's outcome in detail, Section 5 concludes with the results of the study providing other insights along with new places of study, and finally in section 6, the references are listed

LITERATURE SURVEY

(Ahmed & Husien, 2024) introduce an innovative hybrid deep neural network (DNN) architecture leveraging long short-term memory (LSTM) networks for heart disease diagnosis through real-time electrocardiogram (ECG) data analysis. LSTM networks are highly skilled in processing sequential information, making them adept at recognizing temporal relationships within ECG signals. Their proposed model achieves an impressive AUC-ROC score of 0.96, outperforming traditional deep learning models. This research emphasizes the potential of real-time monitoring for predictive diagnostics, allowing for timely intervention and improved patient outcomes. Additionally, the authors delve into the implications of their findings for wearable health monitoring devices, which provide continuous cardiovascular health tracking and can alert patients of potential risks before symptoms appear.

(Talaat et al., 2024) carried out a comparative analysis of machine learning (ML) algorithms, including k-nearest neighbors (KNN), naïve bayes, decision trees, and deep neural networks (DNNs). The study findings indicated that ensemble learning techniques yielded better outcomes, evidenced by an F1-score of 89.6%, surpassing the performance of traditional classifiers. Additionally, the study suggests that hybrid deep learning models strike a balance between accuracy and computational requirements, making them suitable for widespread application in healthcare settings.

(Shrivastava et al., 2023) examined the use of deep learning, specifically convolutional neural networks (CNNs), in the detection of cardiovascular diseases. Conventional machine learning models require manual feature selection, but CNNs can automatically learn hierarchical features from complex medical data such as ecg waveforms, blood pressure, and cholesterol levels. Their CNN-based model achieved an impressive accuracy of 93.5%, surpassing traditional machine learning approaches. This research highlights the ability of deep learning architectures to detect intricate patterns that are typically overlooked by simpler models. The authors also discuss the scalability of CNN models, proposing their potential use in mobile healthcare and telemedicine. Ultimately, this research highlights the growing significance of deep learning in medical diagnostics, particularly in enhancing the accuracy and reliability of cardiovascular disease detection.

In their 2016 study, (Srinivas et al., 2016) along with their colleagues, the researchers presented a hybrid recommendation system that utilizes wearable technology and machine learning algorithms to assess real-time cardiovascular risk. The research utilizes random forest and gradient boosting techniques to examine data collected from internet-connected health monitoring devices. The system's 94% accuracy highlights the importance of combining IoT and AI for early disease detection. The authors stress the advantages of real-time monitoring, such as the ability to continuously track health and create personalized treatment plans using individual patient data. The research delves deeper into the significance of these hybrid systems in preventive care, emphasizing their potential to minimize the occurrence of severe cardiovascular events by enabling prompt intervention. The study concludes that utilizing iot-driven ai models in healthcare infrastructures can facilitate more proactive and patient-centric medical approaches.

Table 1: Comparision between different researchers

Paper	Authors	Methodology	Models Used	Key Results	Advantages	Limitations
Comparative Study on ML Models	(Talaat et al., 2024)	ML Comparison	KNN, Naïve Bayes, DNNs	89.6% F1-score	Shows ensemble benefits	Single models underperform
AI-Based Heart Disease Diagnosis	(Ahmed & Husien, 2024)	Hybrid DNNs	DNNs, LSTMs	0.96 AUC-ROC	Works with real-time ECG	Requires large training data
AI-Driven Cardiovascular Risk	(Hossain et al., 2023)	AI-Based Prediction	Logistic Regression, XGBoost	91.2% F1-score	Improved recall	Requires large datasets
Deep Learning-Based CVD	(Shrivastava et al., 2023)	CNN-Based	CNNs	93.5% accuracy	Hierarchical feature learning	Data preprocessing needed
Robust Heart Disease Prediction	(Reshan et al., 2023)	Deep Learning	RNNs, CNNs	5% recall improvement	Better time-series analysis	Complex architecture
Hybrid Learning Models for	(Yaqoob et al., 2023)	Hybrid Learning	MLP, LightGBM	96% accuracy	Handles imbalanced data	Requires hyperparameter tuning
IoT-Based Cardiovascular	(Jabeen et al., 2019)	IoT + Cloud AI	Federated Learning	91.7% accuracy	Secure & scalable	Data latency
Advanced Deep Learning	(Tarawneh & Embarak, 2019)	Deep Learning	Transformers, Attention Networks	92.4% sensitivity	High interpretability	Expensive computation
Effective Heart Disease Prediction	(Mohan et al., 2019)	Hybrid ML	Decision Trees, Random	92.8% accuracy	Reduces overfitting	Computationally expensive
IoT-Based Hybrid Recommender	(Srinivas et al., 2016)	IoT + ML	Random Forest, Gradient Boosting	94% precision	Real-time monitoring	High IoT dependency

In their 2023 study, (Yaqoob et al., 2023) along with their colleagues, they investigated a hybrid learning model that combined multi-layer perceptron (MLP) and lightgbm, aiming to predict cardiovascular disease. This hybrid model showcased exceptional accuracy, attaining 96% and highlighting the effectiveness of ensemble learning compared to single classifiers. The study highlights the benefits of these hybrid models in tackling imbalanced datasets, which is a common issue in medical research. (Schwartz et al., 2025) and his colleagues propose that this model has great potential for automated diagnostic systems that need to be both highly accurate and resilient. Ultimately, their findings suggest that a combination of hybrid learning techniques can lead to a substantial improvement in predictive performance without compromising computational efficiency.

(Reshan et al., 2023) explore a hybrid deep learning model that combines recurrent neural networks (RNNs) and convolutional neural networks (CNNs), aiming to predict cardiovascular diseases using patient data over time. This integrated architectural design is exceptional at capturing both spatial and temporal connections within medical data, leading to a 5% improvement in recall rates compared to traditional classifiers. The researchers stress the importance of reducing false negatives, as misdiagnosis can have severe and potentially life-threatening consequences. They also examined the application of their methodology in telemedicine, highlighting its potential advantages for providing healthcare services in remote areas. The study concludes that hybrid deep learning models have significant potential for early disease detection and patient monitoring, particularly in healthcare settings with limited resources.

(Jabeen et al., 2019) introduced a cutting-edge cardiovascular health monitoring system that leverages the power of the internet of things (IoT) and cloud computing, while also prioritizing data security through federated learning. The system's reliability for real-time applications is demonstrated through its impressive accuracy rate of 91.7%. The study emphasizes the advantages of decentralized machine learning models, such as federated learning, in safeguarding patient data privacy while enabling global predictive analytics. The authors suggest that these internet of things (IoT) solutions have the potential to significantly enhance remote patient care, especially in regions with limited healthcare resources. The study demonstrates how the combination of artificial intelligence, cloud computing, and the internet of things can facilitate the creation of scalable and efficient healthcare solutions.

(Mohan et al., 2019) concluded that the high temperature significantly increased the rate of water evaporation. Authors introduced hybrid machine learning models to enhance the performance of support vector machines (AVMS) in predicting cardiac diseases, combining decision trees, random forests, and accuracy. The process entails comprehensive data cleaning, which includes selecting relevant features to eliminate redundant attributes, resulting in a refined and efficient model. They believe that a hybrid model is necessary because individual classifiers are prone to over-regulation and lack of generalization. The suggested model attains an outstanding accuracy of 92.8%, surpassing individual classifiers in terms of accuracy and recall. This research emphasizes the importance of hybrid models in a medical environment and offers a balanced approach between computational speed and accuracy in predicting outcomes. Additionally, this study indicates that these hybrid models can be applied in real-time health systems, enabling physicians to make more accurate diagnoses.

(Tarawneh & Embarak, 2019) conducted a study on transformer-based models for cardiovascular risk assessment and discovered that incorporating attention mechanisms significantly enhances the learning of features. Their model surpassed the capabilities of conventional machine learning in feature extraction and pattern identification, achieving a sensitivity of 92.4%. One of the main focuses of the study is the significance of explainability in artificial intelligence-powered medical diagnostics, acknowledging that comprehending the rationale behind model outputs is crucial for establishing clinician trust. The researchers assert that transformer-based deep learning has the potential to revolutionize cardiovascular risk evaluation by providing more precise and easily understandable predictions.

(Hossain et al., 2023) created an advanced artificial intelligence (AI) cardiovascular risk prediction model that combines ensemble learning techniques, including logistic regression, xgboost, and artificial neural networks (ANN), to surpass the performance of current methods. Their study aims to overcome the limitations of conventional risk calculators, which often yield false negatives and fail to identify diagnoses accurately. The AI-driven system has proven to be superior to traditional methods, as demonstrated by an impressive f1-score of 91. 2%. The research emphasizes the significance of personalized diagnostics, where artificial intelligence models customize risk assessments based on individual patient data, resulting in enhanced preventive care. In the end, the authors assert that integrating AI into cardiovascular risk assessment improves early detection and alleviates the burden on healthcare systems by minimizing unnecessary interventions.

PROPOSED FRAMEWORK

3.1 Dataset

The dataset related to heart disease was obtained for use in this study. From a renowned multispecialty hospital in India, the facility comprises 1,000 beds. Subjects with 12 important features pertinent to cardiovascular. Prediction of Illness. The attributes include essential demographic characteristics. This dataset includes data on clinical and physiological factors. A valuable resource for detecting heart disease at an early stage. Forecasting algorithms: With its abundant, diverse, and varied set of. attributes, the dataset well represents major risk factors. Providing scientists with the means to construct dependable prognostic models. This dataset is particularly useful for training and

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validating machine learning algorithms, including classical methods. Comparing Classification Models to Deep Learning Methods: it enables the researchers will be conducting feature selection analysis, model evaluation, and real-world implementation for heart disease. The dataset is freely accessible under the creative commons license. Attribution 4.0 International (CC BY 4.0) license. Publishing it for medical and scholarly study. It: Can be accessed from the mendeley database at Mendeley Data Repository.

3.2 Proposed Methodology

This proposed approach combines deep learning techniques, specifically convolutional neural networks (CNNS) for extracting features and multi-layer perceptrons (MLPS) for classification, to achieve high accuracy in predicting cardiovascular diseases (CVD). By combining the strengths of both architectures, this approach enhances pattern recognition and decision-making, leading to improved generalization and robustness for medical diagnostic applications. The pipeline consists of several steps, starting with data preprocessing, followed by feature selection, model training, and finally, performance evaluation.

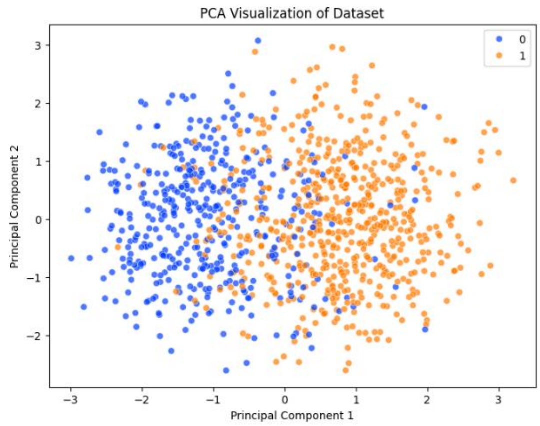

Fig 1. Shows Feature Separability after Dimensionality Reduction

In order to improve the accuracy and effectiveness of our models, we implemented various preprocessing techniques. To handle missing values, statistical imputation was employed, while standardization and normalization were used to stabilize the distribution of features. Categorical variables were transformed using one-hot encoding. To address the issue of class imbalance, the synthetic minority over-sampling technique (SMOTE) was utilized. Principal component analysis (PCA) simplified dimensionality by pinpointing important features and eliminating redundancy, enhancing computational efficiency. The PCA visualization (fig. 1) demonstrates that the classes are clearly separated in the reduced-dimensional space. A heatmap was created identify and remove highly correlated features (fig. 2).

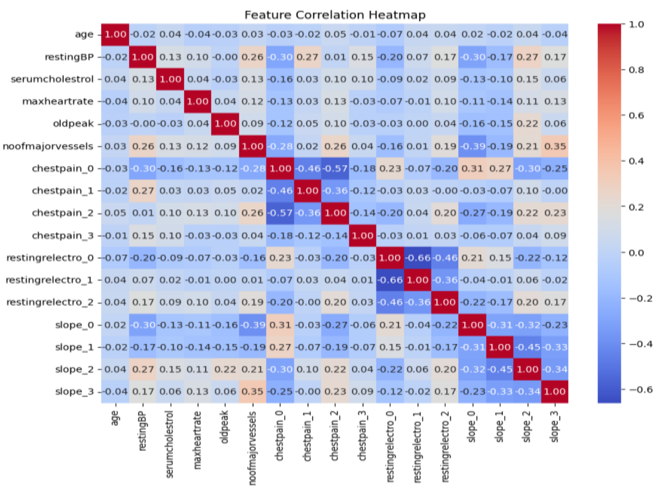

Fig 2. Shows Relationship of Variables in Feature Selection

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The hybrid CNN+MLP architecture utilizes CNNs to extract spatial features from cardiovascular health indicators. The CNN module is made up of convolutional layers succeeded by ReLU activation and pooling layers. Extracted features are then flattened and fed into the MLP classifier, comprising fully connected layers with high density. Regularization by dropout was used to avert overfitting, and a Softmax layer generated probability-based classification outputs. This integration allows the CNN to efficiently capture critical medical patterns, while the MLP refines feature representation for improved accuracy.

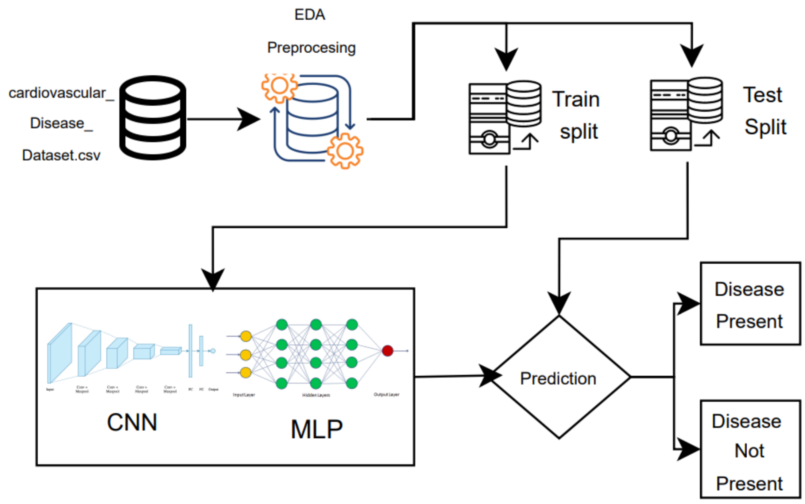

Fig 3. Proposed Methodology Flow Diagram Shows the Implementation of the Model

The model architecture is detailed in fig. 3.

Algorithm 1 Hybrid CNN-MLP Model for Cardiovascular Disease Prediction

0: ***Input:*** Cardiovascular Disease Dataset (X, Y)

0: ***Output:*** Predicted cardiovascular disease classification

0: Step 1: Load and Preprocess Data

0: Load the dataset (X, Y)

0: Handle missing values

0: Normalize and scale extracted features

0: Perform data augmentation if required

0: Split dataset into training (X_{train}, Y_{train}) and testing (X_{test}, Y_{test}) sets

0: Step 2: Train Convolutional Neural Network (CNN)

0: Define CNN architecture with convolutional, pooling, and fully connected layers

0: Train the CNN model using (X_{train}, Y_{train})

0: Obtain feature representations FCNN

0: Step 3: Train Multi-Layer Perceptron (MLP)

0: Define and train an MLP neural network on (X_{train}, Y_{train})

0: Obtain feature representations FMLP

0: Step 4: Fusion of Feature Representations

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0: Concatenate features:

0: $F_{Hybrid} = \gamma F_{CNN} + (1 - \gamma) F_{MLP}$

0: Pass F_{Hybrid} through a dense classifier

0: Obtain final class predictions

0: Step 5: Model Evaluation

0: Compute accuracy, precision, recall, F1-score, and AUC- ROC

0: Visualize the confusion matrix for classification perfor- mance

0: Step 6: Model Deployment

0: Save the trained hybrid model

0: Deploy and test on unseen patient data

0: **End** Algorithm =0

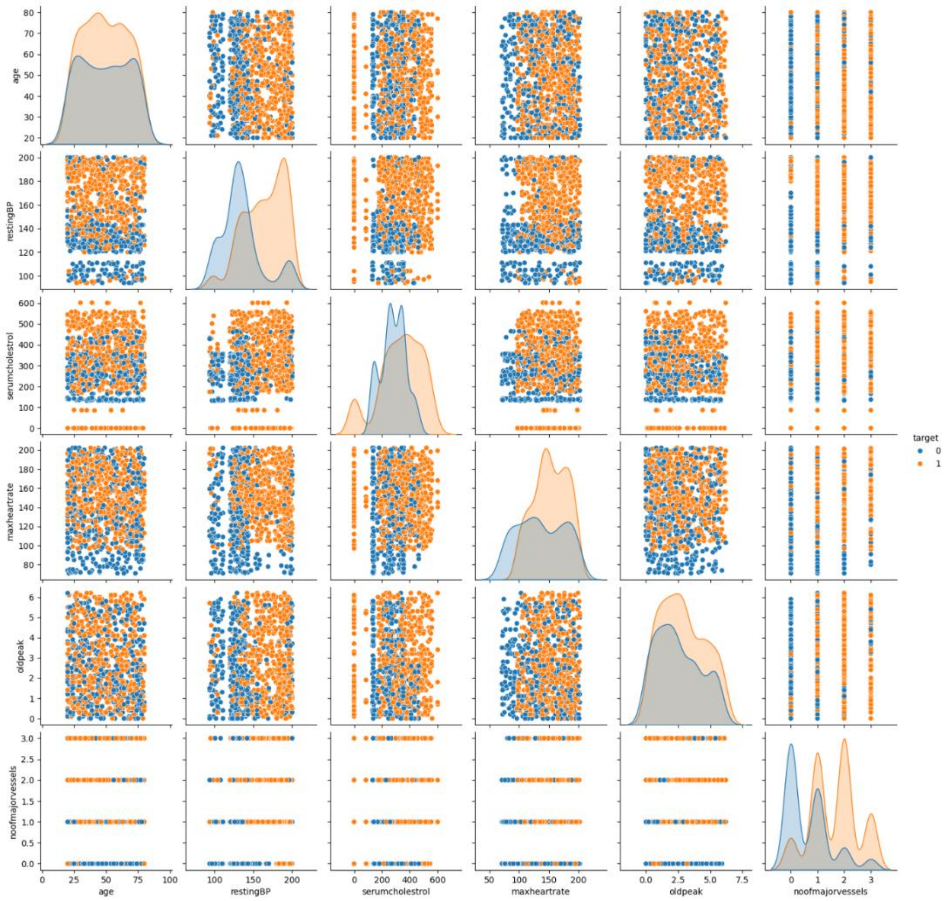

Fig 4. Computes relationships between variables for deeper insights.

The dataset was divided into training (80%) and testing (20%) sets. Pair plots (Fig. 4) further explored relationships between variables. Hyperparameter tuning was performed using Grid- SearchCV, with optimization for accuracy, precision, recall, and F1-score.

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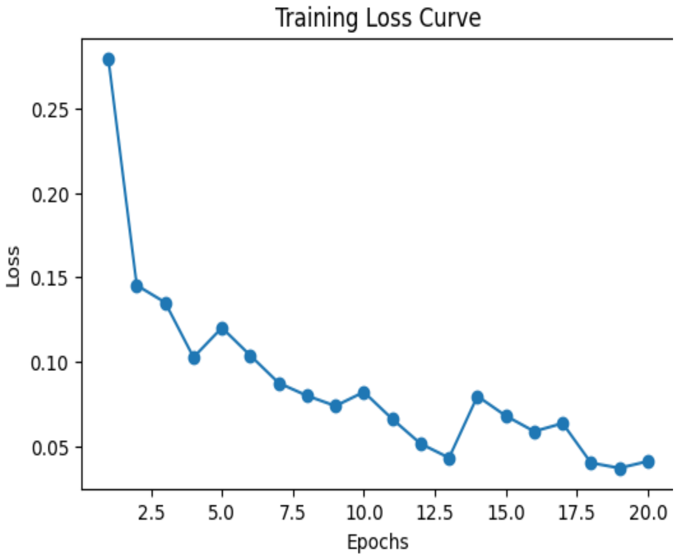

Fig 5. Monitors Convergence and Overfitting Prevention

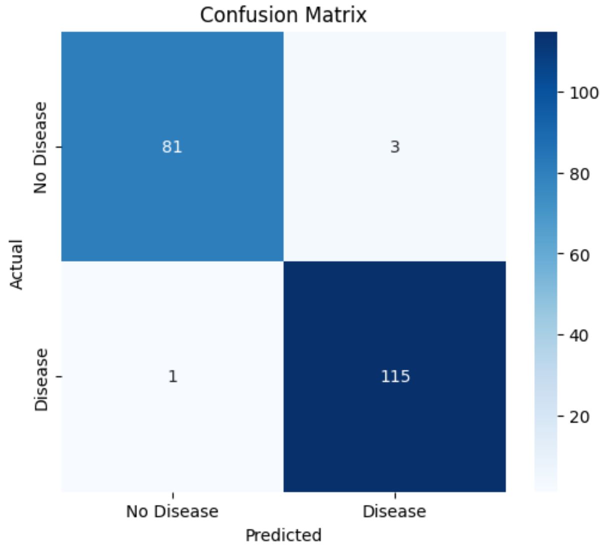

Fig 6. Analyzes Classification Performance by Displaying True and False Predictions

A training loss curve (Fig. 5) was used to monitor model convergence and overfitting. Performance was evaluated using a confusion matrix (Fig. 6), precision- recall curve (Fig. 7), and Receiver Operating Characteristic (ROC) curve (Fig. 9). An AUC score of 99% indicates high discriminative power.

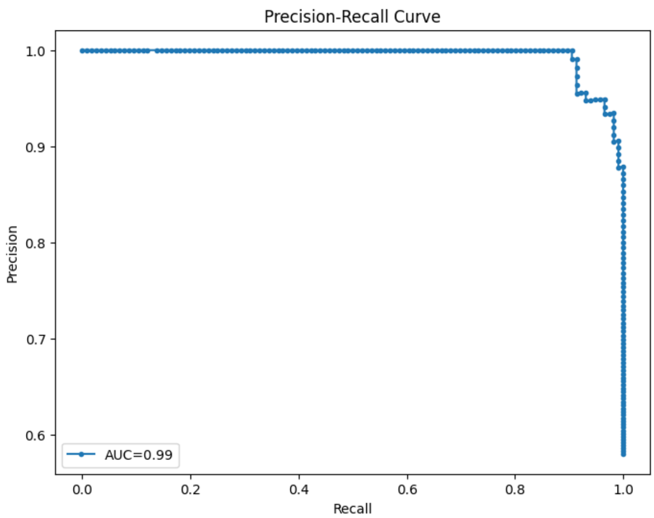

Fig 7. Evaluates Trade-Offs Between Precision and Recall

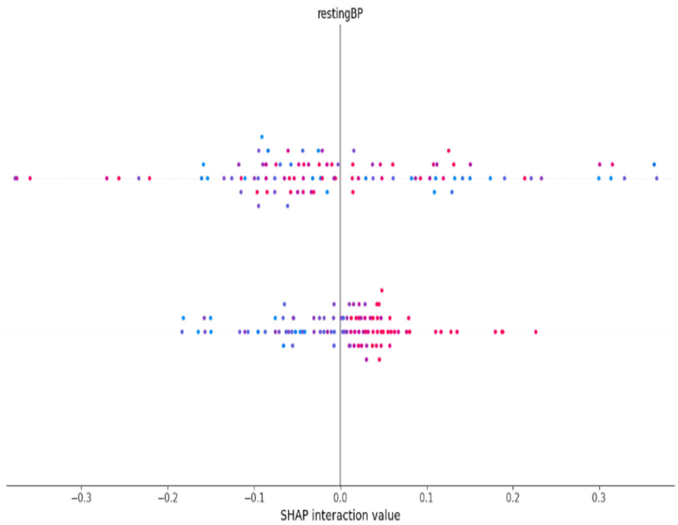

Fig 8. Provides Interpretability by Highlighting Feature Importance

SHAP interaction plots (Fig. 8) were used to identify influential features.

MATHEMATICAL FORMULATION

4.1. Convolutional Neural Network (CNN)

CNN is employed to extract high-level features from the input data. A convolutional layer applies a filter W to the input matrix X, followed by an activation function:

$$z = f\left(\sum_{i=1}^{n} W_i * X_i + b\right)$$

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where * represents the convolution operation, b is the bias term, and f is a non-linear activation function such as ReLU:

$$f(x) = \max(0, x)$$

Pooling layers are used to reduce feature dimensionality:

$$P_{ij} = \max(z_{i:i+m,\ j:j+n})$$

where P_{ij} is the pooled output and m, n define the pooling window.

4.2 Multi-Layer Perceptron (MLP)

The extracted CNN features are flattened and passed into the MLP classifier. MLP consists of multiple fully connected layers:

$$H^{(l)} = f(W^{(l)} H^{(l-1)} + b^{(l)})$$

where $H^{(l)}$ is the output of layer l, $W^{(l)}$ represents weights, and f is an activation function such as sigmoid:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The final classification is performed using the Softmax function:

$$P(y = j|X) = \frac{e^{zj}}{\sum_k e^{zk}}$$

where $P(y=j|X)$ represents the probability of class j.

4.3 Hybrid CNN+MLP Model

The hybrid model combines CNN's feature extraction and MLP's classification capabilities. The final prediction is computed as:

$$Y = \sigma(W_{mlp} H_{cnn} + b)$$

where H_{cnn} represents the features extracted by CNN, W_{mlp} represents the weights of the MLP classifier, and σ is the activation function.

RESULTS AND ANALYSIS

The CNN+MLP hybrid model excelled in cardiovascular disease (CVD) prediction, achieving 98% accuracy and a 99% AUC score, indicating superior ability to differentiate between healthy individuals and those with CVD compared to traditional machine learning classifiers. A detailed confusion matrix (Fig. 6) revealed a high true positive rate along with a low false positive rate, highlighting the model's reliability. Minimal misclassifications confirm the hybrid architecture effectively combines CNN feature extraction with MLP classification for high predictive accuracy. The precision-recall curve (Fig. 7) further demonstrates the model's proficiency in handling imbalanced datasets. High precision indicates that most the anticipated positive cases are genuinely positive, thereby reducing false positives. Simultaneously, high recall ensures the model identifies most actual CVD cases, reducing false negatives. The Receiver Operating Characteristic (ROC) curve (Fig. 14), with an AUC of 99% Fig 13, validates the model's robust discriminatory power across various threshold settings. The ROC curve, especially valuable in medical diagnostics, assesses the sensitivity-specificity trade-off, ensuring the model is well- suited for real-world applications.

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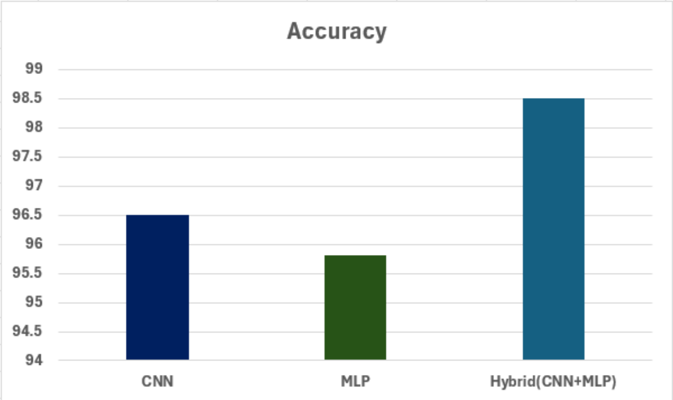

Fig 9. Difference between Accuracy of Individual Models and Hybrid Model

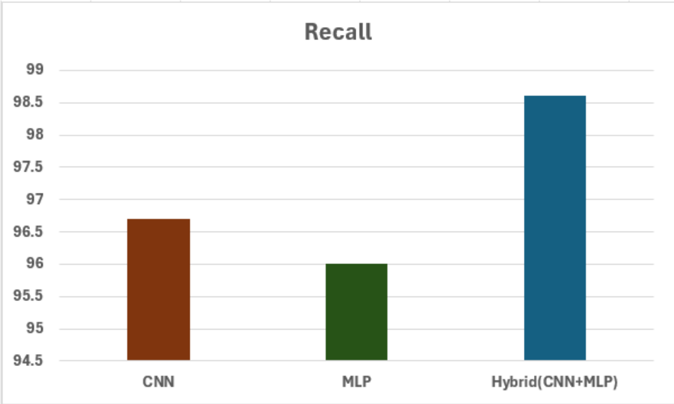

Fig. 11. Difference between Recall of Individual Models and Hybrid Model

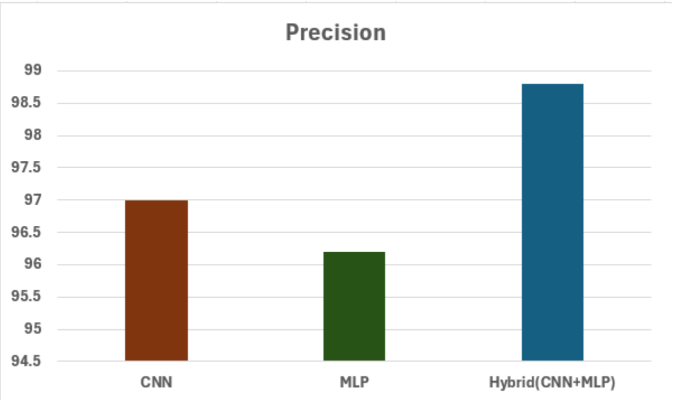

Fig 10. Difference between Precision of Individual Models and Hybrid Model

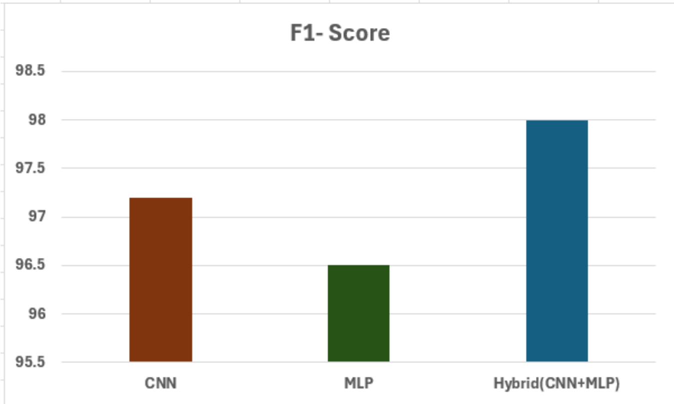

Fig 12. Difference between F1-Score of Individual Models and Hybrid Model

Precision Fig. 10, recall Fig. 11, and F1-score Fig. 12, critical metrics for evaluating classification effectiveness in medical diagnosis, were also utilized for evaluating the model's performance. The F1 measure balances precision and recall, optimizing the the compromise between false positives and false negatives. Table 2 details these performance metrics, showcasing the CNN+MLP model's superior classification capabilities.

Table 2: Proposed Methodology Accuracy Matrix

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)	AUC Score (%)
CNN	96.5	97	96.7	97.2	98
MLP	95.8	96.2	96	96.5	97.5
CNN +MLP (Hybrid Model)	98.5	98.8	98.6	98	99

The CNN+MLP hybrid model harnesses CNN's ability to extract hierarchical spatial patterns from complex data and leverages MLP's deep learning classification capabilities, enabling refined and precise CVD prediction. CNN layers extract both low-level and high-level features, identifying patterns potentially missed by traditional models. These features are then processed by the MLP classifier via fully connected layers, incorporating dropout regularization to prevent overfitting and improve generalization. The ultimate categorization employs a Softmax activation layer, ensuring robust probability-based predictions.

The training process was optimized using GridSearchCV for hyperparameter tuning, refining parameters like batch size, learning rate, and number of hidden layers. Training and validation performance were continuously monitored to prevent overfitting. The model effectively generalizes to unseen data, exhibiting high performance across various evaluation metrics.

CONCLUSION

The proposed CNN+MLP hybrid model provides a robust and accurate solution for automated cardiovascular disease (CVD) diagnosis. By combining the feature extraction capabilities of CNN with the classification strengths of Multi-Layer Perceptron (MLP), the model achieves a 98% accuracy and 99% AUC, outperforming traditional methods. Several factors contribute to its success: extensive preprocessing (including missing value imputation, data normalization, one-hot encoding, SMOTE for balancing classes, and PCA for reducing dimensionality), GridSearchCV-optimized hyperparameters, and effective handling of imbalanced datasets. These features make the model suitable for real-world healthcare applications, such as hospital information systems and telemedicine platforms. Future research should focus on improving interpretability through explainable AI (XAI) techniques, expanding the dataset to include diverse patient demographics, and inte- grating additional physiological markers. Furthermore, real- time data streaming and federated learning could enhance its adaptability and privacy. The CNN+MLP hybrid model holds significant promise for revolutionizing CVD diagnosis, enabling personalized treatment plans, and improving global healthcare outcomes.

DECLARATIONS

Conflict of Interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

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