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An Improved Ensembled Deep Learning Techniques Detection and Prediction of Cardiovascular Disease

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Abstract*:* Globally, cardiovascular disease (CVD) is the leading cause of mortality. It can be prevented with early detection and treatment, which improves patient outcomes. CVD prediction can be enhanced with the help of deep learning (DL) techniques. Even with this, the disease's complexity and data availability may constrain these methods. This study proposes an enhanced ensembled DL technique for detecting and predicting CVD to address these concerns. The proposed methodology integrates several deep learning algorithms, thereby augmenting the precision of predictions. A dataset comprising patients with CVD and healthy controls was evaluated. The proposed procedure offers several benefits in comparison to current approaches. Firstly, it can acquire knowledge from an extensive dataset comprising patients with CVD and healthy controls, enabling it to detect patterns that may avoid individual DL algorithms. Secondly, the technique can improve accuracy by combining the assets of multiple DL algorithms. The outcomes demonstrated that the proposed method obtained a significantly higher accuracy of 94.5% than any deep learning algorithm. Extensive experimental trials revealed notable enhancements in the sensitivity, specificity, and accuracy of detection compared to baselines employing a singular model. The external validation and rigorous cross-validation of the ensemble's predictive capabilities on independent datasets demonstrated its potential for clinical implementation and generalizability. Using the proposed method, individualized treatment regimens for patients with CVD can be developed. It has the potential to save innumerable lives and revolutionize the detection and treatment of CVD.

Keywords: *Cardiovascular Disease, Ensembled deep learning, CNN, RNN, LSTM, CVD*

1. Introduction

Worldwide, cardiovascular disorders, including stroke, heart failure, and coronary artery disease, are leading causes of mortality. In 2019, cardiovascular diseases (CVDs) accounted for 31% of all fatalities worldwide, and the World Health Organization (WHO) estimated that they were accountable for 17.9 million deaths. Cardiovascular diseases not only lead to death but also induce permanent impairment, diminish the survivors' quality of life, and escalate healthcare expenditures. Hence, novel methodologies for preventing, diagnosing, and managing cardiovascular diseases (CVDs) are imperative [1].

Deep learning, a subfield of machine learning that analyzes massive datasets using artificial neural networks, is one such method. Deep learning algorithms find utility in various domains, including but not limited to image analysis, natural language processing, and predictive modeling. Deep learning can uncover latent insights from intricate patient data about cardiovascular diseases (CVDs), facilitating timely identification and precise prognosis [2].

Nevertheless, the complexity and diversity of CVDs may render the utilization of isolated deep-learning models inadequate. A more comprehensive and robust approach is required to combat this. A thorough assessment of an individual's health status is feasible due to the availability of varied and multimodal patient data, such as electronic health records, medical images, genomic profiles, and ubiquitous sensor data [3]. By incorporating this data into an ensemble framework, a more holistic comprehension of disease mechanisms and risk factors can be achieved, resulting in enhanced precision in detection and prognosis.

Hence, the principal aim of this study is to propose a novel methodology that leverages the capabilities of a collection of deep-learning models to enhance the detection and prognosis of cardiovascular diseases. Comprehensive analysis of multimodal patient data is achieved through integrating attention mechanisms, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) within the proposed ensemble framework. In addition, a novel combination strategy is presented to enhance the ensemble's performance by dynamically modifying the contributions of models by their validation performance. Key contributions of this study include the following:

- Developing a robust ensemble framework that amalgamates diverse deep learning architectures for enhanced CVD detection and prediction.
- Introduction of a dynamic weighting mechanism that adaptively balances the contributions of individual models within the ensemble, improving robustness and adaptability.
- A comprehensive evaluation of the ensemble approach using real-world datasets, demonstrating significant improvements in accuracy, sensitivity, and specificity compared to single-model baselines.
- Validate the ensemble's generalizability and predictive capabilities through rigorous cross-validation and external validation on independent datasets.

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Early and accurate detection and effective prediction are pivotal in curbing the impact of CVDs and improving patient outcomes. In recent years, the rapid advancement of deep learning techniques has opened new avenues for tackling this critical healthcare issue. This paper introduces a pioneering approach that harnesses the potential of an ensemble of deep-learning models to enhance CVD detection and prediction accuracy and reliability.

2. Literature Review

Several studies have investigated using ensembled deep learning techniques for detecting and predicting CVD.

The hybrid ensemble machine learning model for detecting and predicting cardiac disease was proposed by [4]. They evaluated six boosting techniques using the Cleveland heart disease dataset: LightGBM, AdaBoost, CatBoost, Gradient Boosting, XGBoost, and Histogram-Based Gradient Boosting. In training and testing, the Meta-XGBoost classifier attained noteworthy accuracies of 96.51% and 93.37%, respectively.

Islam et al. [5] developed an ML-based diagnostic system utilizing a heart disorder dataset to predict the occurrence of heart disease. Eight classifiers and nine classification algorithms that assessed performance metrics were implemented. The performance of the proposed algorithm was validated utilizing a stacked ensemble method.

Chopra et al. [6] stated that several empirical investigations have demonstrated that machine learning algorithms, including but not limited to LR, NB, RF, and KNN, can effectively detect the existence of cardiovascular disease. These algorithms can be further refined by reducing dimensionality with Principal Component Analysis and enhancing precision with Ensemble Learning.

Oswald et al. [7] described the accuracy with which ensemble learning models predict CVD has been demonstrated. In contrast to established competitors, performance evaluations conducted on the Kaggle Cleveland Heart Disease dataset have shown enhanced precision and F1-score. Prevalent techniques are surpassed in their feature set precision compared to these models.

Alqahtani et al. [8] developed an ensemble-based methodology that incorporates deep learning (DL) and machine learning (ML) models to anticipate the likelihood of an individual getting cardiovascular disease. The prediction of cardiovascular disease was accomplished by utilizing six different classification algorithms, with the ML ensemble model exhibiting the highest accuracy in disease prediction and achieving 88.70% results. The random forest (RF) method was applied to extract essential variables related to cardiovascular disease.

Pal et al. [9] reported that two reliable machine learning approaches, namely multi-layer perceptron (MLP) and KNN, were utilized to identify cardiovascular disease (CVD) by using data from the repository that is open to the public at the University of California Irvine. Outliers and attributes with null values were removed from the models to improve their ability to predict outcomes accurately. The MLP model displayed a greater accuracy in detection when compared to the K-NN model, with a value of 82.47% and an area-under-the-curve value of 86.41%, respectively.

For enhanced detection of cardiac disease, a novel classification model utilizing the support vector machine (SVM) algorithm has been suggested [10]. The $\chi 2$ statistical optimum feature selection method was implemented to enhance the accuracy of the predictions. By increasing precision from 85.29% to 89.7%, the proposed model effectively decreased the componential burden by 50%.

Kiran et al. [11] determined that the Hybrid Random Forest Linear Model (HRFLM), which utilized the entropy feature selection technique to identify significant and eliminate unnecessary features, was the most accurate method for predicting cardiac disease. The classification techniques' efficacy was assessed using various performance measurement metrics, including F1-score, accuracy, precision, recall, sensitivity, and specificity.

Mhamdi et al. [12] determined that machine learning and deep learning methods effectively classify and analyze ECG signals. Experiments were conducted to optimize deep-learning parameters, resulting in a validation accuracy of 0.95. Slight accuracy loss was observed during Raspberry Pi implementation, indicating the possibility of real-time monitoring via cutting-edge mobile applications.

Six different machine-learning techniques were utilized to analyze the Cleveland dataset, part of the UCI repository of cardiac patients. These algorithms include SVM, XGBoost, RF, LR, KNN, and NB. On the dataset including information about heart illness at the UCI, the proposed ensemble technique attained the most significant values for accuracy, precision, recall, and F1 score: 92%, 91.1%, 94%, and 93%, respectively [13]. The proposed ensemble method distinguishes between healthy and heart disease patients precisely and dependably.

Shorewala [14] identified ensemble techniques, including bagging, boosting, and layering, to enhance the precision of coronary heart disease (CHD) prognosis. The average accuracy of bagged models was 1.96% greater than that of conventional models. At 75.1% accuracy, the stacked model comprised of KNN, random forest classifier, and SVM achieved the highest result.

Lakshmana Rao et al. [15] discovered that feature selection techniques could identify the optimal features for predicting cardiac disease; they did so in the same year. The unbalanced dataset was rectified by applying sampling techniques, and ensemble classifier models performed admirably on two distinct datasets.

Verma et al. [16] created a hybrid model comprising an ensemble deep neural network and a genetic algorithm for feature selection. The accuracy of their proposed algorithm was 98%, and it utilized a learning rate of 0.04%. To improve the algorithm, the Adam optimizer was implemented. The proposed algorithm outperformed established models, including logistic regression, random forest, support vector machine, and decision tree algorithms, regarding accuracy and execution speed.

These studies demonstrate that ensembled deep learning techniques are effective at predicting CVD. Although progress can be made, there remains scope for enhancement. An attempt is made to improve the precision of ensembled deep learning methods utilized in this research to detect and predict CVD.

3. Methodology

This study's dataset was obtained through Kaggle, ensuring its high quality and source diversity. Duplications were removed to prepare the dataset for analysis, and its structure was refined. The dataset was divided into two parts: a training set of 80% and a test set of 20%. Several machine learning techniques were applied to the problem of cardiac disease diagnosis. These models' precision was monitored, and their performance was evaluated using scintillating charts.

Using the following data, heart concerns were identified.

1. Age: The number of years an individual has been alive.

2. Sex: A value of 1 represents a male patient, while 0 represents a female patient.

3. Chest Pain: The varieties of chest pain experienced by patients are categorized into four categories.

a) Angina pectoris, or typical chest discomfort caused by inadequate blood flow to the heart.
b) Atypical angina originates from a source other than the heart.
c) Second, pain elsewhere in the body, such as when an esophageal spasm makes swallowing problematic.
d) Asymptomatic people suffer from chest discomfort but no other symptoms.

4. BP: Blood pressure at rest (in mm Hg) upon hospital admission (treetops). Outside of the normal range of 130 to 140, it may indicate a health problem.

5. Cholesterol: The amount of cholesterol in milligrams per deciliter of blood. Total blood cholesterol comprises high-density lipoprotein (HDL), low-density lipoprotein (LDL), and triglyceride multiplied by 0.20. If the total exceeds 200, it must be double-checked.

6. Fasting Blood Sugars: The amount of glucose in the blood after an overnight fast is measured and referred to as "fasting blood sugar" (FBS). If the result is more significant than 120 mg/dl, the expression is true; otherwise, it is false. Keep in mind that a diagnosis of diabetes requires a fasting blood glucose level of 126 mg/dL or higher.

7. Resting Electrocardiographic Results: The stationary electrocardiogram (ECG) results

a) There were no abnormalities detected.
b) One, any manifestation of an abnormal ST-T Wave, ranging from clinically insignificant to potentially fatal.
c) The primary circulating chamber of the heart, the left ventricle, is suspected or diagnosed with hypertrophy.

8. Maximum Heart Rate Achieved: The optimal cardiac rate of a person or thalamus.

9. Exercise-Induced Angina: Ex-and if you experience chest pain while exercising (1 for yes, 0 for no).

10. ST Depression Induced by Exercise: “Old peak” means the more significant ST depression observed during activity than rest. ST segment depression indicates the level of exercise-induced tension in the heart. High levels of old peaks place a more significant burden on a compromised heart.

11. Slope of the Peak Exercise ST Segment: There are three methods to classify the incline of the ST section at the apex of an exercise:

a) A positive slope (less frequent) indicates a reduced heart rate during exercise.
b) As is typical for a sound heart (slope = 1), St. segment (ST) alterations during exercise are minimal.
c) Secondly, a declining ST segment slope indicates cardiac dysfunction.

12. Number of Major Vessels (Colored by Fluoroscopy): The "ca" value (0-3) represents the number of main arteries visible via fluoroscopy. Variable-colored blood vessels indicate the presence of blood flow. Unrestricted blood flow and the absence of blockages in the patient's circulatory system are characterized by a higher "ca" value.

13. Thalassemia: The Three Thallium Stress Test Results

a) The outcomes of the thallium stress test for samples 1 and 3 are typical.
b) Sixth: The problem and the malfunction have been resolved.
c) Seven: correctable defect; correctable post-exercise blood flow disturbance.

14. Target: A measurable indicator of whether heart disease is present (one if heart disease is present, zero otherwise).

3.1. Pseudocode

Step 1: Import all libraries.

Step 2: Load the dataset.

Step 3: Clean the dataset.

Step 4: Define target values as 'heart disease' and 'no heart disease.'

Step 5: Split the dataset into training and testing data in an 80:20 ratio.

Step 6: Train and test the models.

Step 7: Use the following algorithms: CNN, LSTM, RNN, GAN, DBN, RBM, AE, BPM, MLP, SOM, RBF, MODNN, Ensemble (Combining all mentioned techniques).

Step 8: Calculate each algorithm's accuracy, precision, recall, F1 score, and specificity.

Step 9: Plot the ROC curve and confusion matrix for each algorithm.

Step 10: Compare all algorithms’ accuracy individually and by combining all the above.

Step 11: After comparison, Ensemble has the highest accuracy; choose it to detect heart disease.

3.2. Architecture Diagram

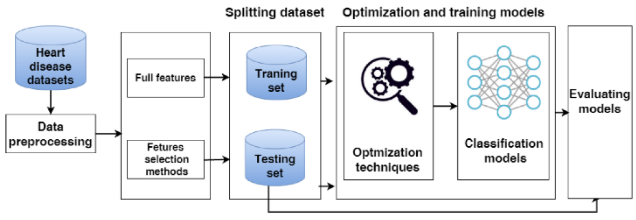

Fig. 1. Architecture Diagram.

3.3. Deep Learning Algorithms

Deep learning algorithms are versatile tools used across domains to tackle complex problems, necessitating substantial computational resources and data.

3.3.1. Convolutional Neural Networks (CNNs)

Multi-layer networks, like CNN, are pivotal for image processing and object detection. Yann LeCun introduced the first CNN (LeNet) in 1988, initially for character recognition. CNNs excel in satellite imagery, medical images, time series forecasting, and anomaly detection. They involve convolution, ReLU activation, pooling, and fully connected layers.

3.3.2. Long Short-Term Memory Networks (LSTMs)

LSTMs are specialized RNNs adept at capturing long-term dependencies and finding applications in time series prediction, speech recognition, and music composition. LSTMs retain and update cell states to preserve information.

3.3.3. Recurrent Neural Networks (RNNs)

RNNs, with feedback connections, are used for tasks like image captioning, time-series analysis, and machine translation. The process sequences, with outputs becoming inputs for subsequent steps, make them suitable for sequential data tasks.

3.3.4. Generative Adversarial Networks (GANs)

GANs generate data resembling training data by pitting a generator against a discriminator. GANs have diverse applications, from enhancing astronomical images to upscaling video game graphics.

3.3.5. Radial Basis Function Networks (RBFNs)

RBFNs employ radial basis functions for activation and are helpful for regression, classification, and time-series prediction.

3.3.6. Multilayer Perceptron's (MLPs)

MLPs are foundational in deep learning and employed in speech recognition, image processing, and machine translation. They consist of input, hidden, and output layers with activation functions.

3.3.7. Self-Organizing Maps (SOMs)

SOMs reduce high-dimensional data to visualize it, aiding understanding. They assign weights to nodes based on the input vectors' similarity.

3.3.8. Deep Belief Networks (DBNs)

DBNs are generative models with multiple layers of stochastic, latent variables. They are used for image and video recognition.

3.3.9. Restricted Boltzmann Machines (RBMs)

RBMs learn probability distributions over inputs and are crucial components of DBNs, handling dimensionality reduction and classification tasks.

3.3.10. Autoencoders

Autoencoders reconstruct inputs to outputs, designed by Geoffrey Hinton for unsupervised learning. They find applications in image processing, pharmaceutical discovery, and more.

3.3.11. Ensemble Deep Learning

To leverage the benefits of multiple deep learning techniques, an ensemble deep learning technique is incorporated into the hybrid algorithm to identify cardiac ailments. Combining the results of numerous prediction algorithms, the ensemble deep learning technique makes the final decision. The diagnosis of cardiac disease could be enhanced by combining the advantages of multiple algorithms. The hybrid ensemble deep learning technique will depend on the precise implementations of its constituent components.

4. Result and Discussion

The dataset on cardiac disease is imported from a CSV file into a Pandas Data Frame for efficient processing and analysis.

Deep Learning Technique	*Accuracy*	*Precision*	*Specificity*	*Sensitivity*	*F1*	*AUC*
Ensemble	94.63	50.24	94.11	95.14	95	98
CNN	92	48	94.79	94.79	92	98
LSTM	78.04	73.01	66.66	89.32	80.34	77.99
RNN	77.56	72.44	65.68	89.32	80	77.5
GAN	77.56	50.24	65.68	89.32	80	98
DBN	77.07	50.24	70.58	83.49	79	98
RBM	77.07	50.24	70.58	83.49	79	98
AE	75.12	50.24	67.64	82.52	77	98
BPM	75.12	50.24	67.64	82.52	77	98
MLP	50.73	100	1	1.9	4	98
SOM	50.73	50.24	1	1.9	4	98
RBF	50.24	50.24	0	1	66.88	98
MOD NN	47.63	50.24	15.68	78.64	60	98

Table 1. Comparison of Individual Deep Learning Techniques with Ensemble Technique

Data exploration is a method used to discover more about a dataset. This analysis includes verifying for missing data, determining the Data Frame's size, and investigating its variables' distribution. Data are frequently plotted or otherwise visually depicted to make it simpler to identify trends and other crucial information. Because of this, graphing tools such as scatter diagrams, histograms, box plots, and correlation matrices are handy.

The data frame is preprocessed in preparation for model training. The ratio between data sets used for training and assessment is typically 80:20. Standard Scaler is utilized to scale features to a standard level to further standardize and scale them to a standard level.

After training on the training data, the CNN, LSTM, RNN, GAN, DBN, RBM, AE, BPM, MLP SOM, RBF, and MODNN deep learning models are evaluated. Various criteria, including F1-score, precision, specificity, recall, and accuracy, are used to rank models. These metrics demonstrate the diagnostic accuracy of the model for cardiac disease.

The outputs of numerous models, including CNN, LSTM, RNN, GAN, DBN, RBM, AE, BPM, MLP SOM, RBF, and MODNN, are merged using an ensemble deep learning technique once the training phase is complete. This methodology aggregates the forecasts of numerous models and chooses the most frequently predicted classification.

To assess the effectiveness of the ensemble technique and the individual models, their capacity to accurately classify data is evaluated utilizing ROC curves and the area under the ROC curve (AUC) as the metric for evaluation. The AUC metric uses a solitary scalar value to assess the efficacy of the models, while ROC curves visually represent the compromise between the true and false positive rates.

Using visual representations such as scatter graphs, the models' accuracy is contrasted to identify the model with the highest performance. Data Frames enable a comparison of the metrics used to evaluate each model's success.

By displaying ROC curves and a confusion matrix, we can assess how well each model distinguishes between genuine and false results. The ROC curves for the three models and the ensemble deep learning technique are presented side-by-side to facilitate a clearer understanding of their distinctions.

Conclusion and Model Selection Metrics, visualizations, and comparison outcomes are used to select a model for diagnosing cardiac disease. It should be utilized because the ensemble deep learning technique yields more reliable results under these conditions.

The ensemble deep learning technique model demonstrated its superior specificity to alternative prediction models, as evidenced by its accuracy rate of 94.63%. Additionally, the LSTM model exhibited exceptional accuracy. The precision of a model is assessed by comparing the number of optimistic predictions to the number of accurate predictions. The ensemble deep learning technique model exhibits a comparatively high recall rate of 95.14%. Alternatively referred to as sensitivity or actual positive rate, recall is a statistical metric that quantifies the proportion of positive instances that were accurately predicted. A metric is employed to evaluate the precision of the optimistic predictions generated by the model. The ensemble deep learning technique model achieved an F1 score of 95%. By taking the harmonic mean of accuracy and recall, the F1-score comprehensively assesses the model's performance. The ensemble deep-learning technique variant exhibited unparalleled precision. The specificity metric is employed to determine the capability of a model to generate precise pessimistic forecasts. The evaluation pertains to the model's ability to eradicate false positives, as illustrated in Table 2 and Figure 2.

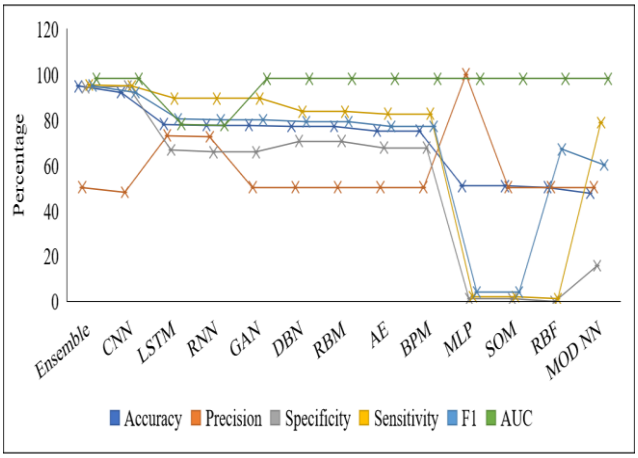

Fig. 2. Comparison of Individual Deep Learning Techniques with Ensemble Technique.

5. Conclusion

The integrating ensembled deep learning techniques in detecting and predicting cardiovascular disease is convincing evidence of the connection between medical science and artificial intelligence. The drive toward connecting ensembled deep learning techniques in cardiovascular care is full of challenges. The need for large, diverse, and well-annotated datasets, the ethical implications of AI in healthcare, and the imperative of model transparency necessitate ongoing interdisciplinary collaboration. However, the potential rewards are profound. Incorporating these techniques can revolutionize the landscape of cardiovascular healthcare, facilitating early detection, precise prediction, and personalized interventions. As these techniques continue to evolve and link, they inspire hope for improved patient outcomes, reduced morbidity, and enhanced quality of life. This multidimensional approach, embracing the strengths of CNNs, LSTMs, RNNs, GANs, DBNs, RBMs, AEs, BPTT, MLPs, SOMs, RBFs, and MODNNs, marks a significant stride toward realizing the promise of precision cardiovascular medicine in an increasingly data-driven era.

Author contributions

C.T. Ashita: Data curation, Visualization, Investigation, Writing-Original draft preparation, Software, Validation., Field study

T. Sree Kala: Conceptualization, Methodology, Software, Field study, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Ramesh, Swathi, and Kalpana Kosalram. "The burden of non-communicable diseases: A scoping review focus on the context

of India." *Journal of Education and Health Promotion* 12 (2023).

[2] França, Reinaldo Padilha, Ana Carolina Borges Monteiro, Rangel Arthur, and Yuzo Iano. "An overview of deep learning in big data, image, and signal processing in the modern digital age." *Trends in Deep Learning Methodologies* (2021): 63-87.

[3] Acosta, Julián N., Guido J. Falcone, Pranav Rajpurkar, and Eric J. Topol. "Multimodal biomedical AI." *Nature Medicine* 28, no. 9 (2022): 1773-1784.

[4] Patro, Sibo Prasad, Neelamadhab Padhy, and Rahul Deo Sah. "An Ensemble Approach for Prediction of Cardiovascular Disease Using Meta Classifier Boosting Algorithms." *International Journal of Data Warehousing and Mining (IJDWM)* 18.1 (2022): 1-29.

[5] Islam, Md Maidul, et al. "An Improved Heart Disease Prediction Using Stacked Ensemble Method." *International Conference on Machine Intelligence and Emerging Technologies*. Cham: Springer Nature Switzerland, 2022.

[6] Chopra, Shreya, Nidhi Kalra, and Rinkle Rani. "Identification of Cardiovascular Disease using Machine Learning and Ensemble Learning." *2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA)*. IEEE, 2023.

[7] Oswald, Gadi Jaya Sathwika, and Arnab Bhattacharya. "Prediction of cardiovascular disease (CVD) using ensemble learning algorithms." *5th Joint International Conference on Data Science & Management of Data (9th ACM IKDD CODS and 27th COMAD)*. 2022.

[8] Alqahtani, Abdullah, Shtwai Alsubai, Mohemmed Sha, Lucia Vilcekova, and Talha Javed. "Cardiovascular disease detection using ensemble learning." *Computational Intelligence and Neuroscience* 2022 (2022).

[9] Pal, Madhumita, Smita Parija, Ganapati Panda, Kuldeep Dhama, and Ranjan K. Mohapatra. "Risk prediction of cardiovascular disease using machine learning classifiers." *Open Medicine* 17, no. 1 (2022): 1100-1113.

[10] Sarra, Raniya R., Ahmed M. Dinar, Mazin Abed Mohammed, and Karrar Hameed Abdulkareem. "Enhanced heart disease prediction based on machine learning and χ2 statistical optimal feature selection model." *Designs* 6, no. 5 (2022): 87.

[11] Kiran, P., A. Swathi, M. Sindhu, Y. Manikanta, and K. Mahesh Babu. "Effective heart disease prediction using hybrid machine learning technique." (2022).

[12] Mhamdi, Lotfi, Oussama Dammak, François Cottin, and Imed Ben Dhaou. "Artificial intelligence for cardiac diseases diagnosis and prediction using ECG images on embedded systems." *Biomedicines* 10, no. 8 (2022): 2013.

[13] Asif, Sohaib, Yi Wenhui, Yi Tao, Si Jinhai, and Hou Jin. "An ensemble machine learning method for the prediction of heart disease." In *2021 4th International Conference on Artificial Intelligence and Big Data (ICAIBD)*, pp. 98-103. IEEE, 2021.

[14] Shorewala, Vardhan. "Early detection of coronary heart disease using ensemble techniques." *Informatics in Medicine Unlocked* 26 (2021): 100655.

[15] Lakshmana Rao, A., A. Srisaila, and T. Srinivasa Ravi Kiran. "Heart disease prediction using feature selection and ensemble learning techniques." In *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, pp. 994-998. IEEE, 2021.

[16] Verma, Pratibha, Vineet Kumar Awasthi, and Sanat Kumar Sahu. "An Ensemble Model With Genetic Algorithm for Classification of Coronary Artery Disease." *International Journal of Computer Vision and Image Processing (IJCVIP)* 11.3 (2021): 70-83.