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Efficient Prediction Model for Cardiovascular Disease Using Deep Learning Techniques

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Abstract

Cardiovascular illness is becoming more commonplace every day, which makes early identification of the condition worrisome and essential. Making a cardiac diagnosis is a challenging procedure that has to be finished fast and expertly. The identification and prediction of cardiovascular illness are vital medical responsibilities that help cardiologists appropriately diagnose and treat their patients. Deep Learning (DL) algorithms have found increasing usage in the medical industry because of their ability to recognize patterns in data. By applying machine learning to categorize the occurrence of cardiovascular illness, clinicians can reduce the rate of misdiagnosis. The goal of this work is to develop an ML model for cardiovascular disease (CVD) forecast based on correlated problems. This research develops a model that can accurately anticipate CVD illnesses, which will reduce the fatality rate from these ailments. This work employs a variety DL approaches to compare the results and analysis of the UCI Machine Learning Heart Disease dataset. We used a benchmark dataset of UCI Heart disease prediction for this work, which consists of 14 different heart disease-related parameters. As DL models, there are Convolutional Nueral Network (CNN), Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM). When compared to DL techniques, the result shows that LSTM offers superior prediction accuracy in less time. 91% accuracy was attained using this LSTM technique. This model performs better on training and testing data. The models were fitted to the test dataset as well as trained on the training dataset to see which fared best. The matrices acquired during this process were accuracy, specificity, sensitivity, Area Under Curve (AUC) and the Receiver Operating Characteristic Curve (ROC).

Keywords: *Deep Learning (DL), Machine Learning (ML), Cardiovascular Disease (CVD), Long Short Term Memory (LSTM).*

Introduction

Due to heart disease's high global death rate, many people now view it as a major health problem. It is a significant duty to identify cardiovascular problems, such as heart attacks, coronary artery diseases, etc., by regular clinical data analysis; early diagnosis of heart disease has the potential to save many lives. One cardiovascular disorder that is particularly well-known for its tendency to result in death is Cardiovascular Disease (CVD) [1]. Over time, plaque accumulation in the CVD, which is mostly caused by fibrin, calcium, and cholesterol. This partial blockage of blood flow originates from the plaques. The use of Deep Learning (DL) [2] and Machine Learning (ML)[3] techniques in the field of medicine has developed dramatically.

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DL is a more well-known ML method. It uses standard tabular data in addition to pictures for classification tasks. ML algorithms may also be used to anticipate the diseases. Make a 2-DNN-based diagnostic system [4]. Resolving the overfitting and underfitting issue is the primary objective of the determination framework. Training data is fed into neural networks (NN). The neural network's functioning is investigated using the testing dataset. Because the proposed model makes use of a DNN with several hidden layers, it outperforms ANN. The accuracy of the prognostic classification for cardiac illnesses will rise with the development of the 2-DNN [5].

Our goal in this study is to find out how well different deep learning algorithms predict cardiac disease. We used a range of methods, including Convolutional Neural Networks (CNN) [6], Artificial Neural Networks (ANNs) [7], and Long Short-Term Memory (LSTM) [8] DL, to create prediction models in order to accomplish this aim. The UCI machine learning repository makes the dataset used in this work accessible to the general audience. Python was used for all of the computation, preprocessing, and visualization. Enhancing the predictive accuracy of cardiac disease is the primary goal of this research. Numerous research have been carried out, with the end goal of limiting feature selection for algorithmic applications.

The rest of the document is arranged as follows: Works pertaining to the heart and the various current methods and methodology are covered in Section II. Our method is described in Section III. Section IV includes results and comments. And Section 5 covers the conclusion.

Recent Studies

The most important part is the heart because it pumps blood to every other part of the body. A malfunctioning heart can cause the mind and other organs to cease working as well, which can cause a person to pass away in a matter of minutes. As a result, proper cardiac function is essential [9]. Heart problems are becoming one of the main reaseons of death worldwide. Because of this, several scholars from all over the world started concentrating on exploiting the enormous datasets to predict heart-related problems. Several ML and DL [10] techniques may evaluate big datasets and yield meaningful findings. These algorithms have become essential for accurately forecasting whether or not cardiac issues will emerge since ML and DL models employ diverse techniques [11].

By learning features from the training data, DL approaches perform better than the extracted features utilised in traditional ML algorithms. Modern architectures include recurrent neural networks (RNN), CNN, LSTM, and gated recurrent units (GRU). Present-day networks have faith in a panacea for illness. The current dataset is subjected to modern architectures such as LSTM [11]–[14] and GRU [15] to evaluate the performance for patient classification of heart ailment. In several respects, coronary angiography is the most precise technique for identifying CVD. Arterial stenosis may be identified from coronary angiography images, and its severity can be evaluated in conjunction with CVD and ACS. But it's an expensive and time-consuming method [16]–[18].

Among these promising methods are artificial neural networks (ANNs), a potent instrument used in ordering tasks and to address other important problems, including signal augmentation, recognition, and component forecast. One important feature of ANNs is their flexibility [19]–[22]. This makes its application possible in scenarios where formal mathematical model development is challenging but a sizable sample size is available. Another important characteristic that helps neural networks solve difficult classification problems is their capacity to generalise input data and offer precise solutions for "unfamiliar" data [23]–[25].

Smart healthcare [26]–[28] is made possible by integration with the Internet of Medical Things (IoMT) [29]–[34]. Patients, carers, and healthcare professionals will have access to the healthcare data that has been stored in the cloud. The recommended framework may be utilised to forecast CVD once the system is calibrated using the feature selection model to determine the feature that will be most helpful for forecasting. The creation of the pooling area curve (PUC) in ML and DL [35]–[38]. This identification based on information is what determines how accurate the forecast will be. This crucial technique has a positive impact on identifying variation in medical images even in the presence of subpar pixels [39], [40].

Methodology

The goal of this study is to assess the probability of CVD using computerized prediction, which will be a helpful tool for patients and healthcare professionals. To do this, we employed a dataset together with a range of ML and DL techniques; the results are shown in this study report.

Data Pre-processing

Table 1: Features of the dataset

S. No.	Attribute	Desc.	Type
1	age	Age of patient in years [29 to 77]	Numeric
2	Sex	Gender of Patient [Male-0, Female-1],	Nominal
3	cp	Chest paint type categories into 4 values [Angina, abnang, notang, asympt]	Nominal
4	trstbps	Resting Blood Pressure in mm hg [Value range 94 -200]	Numeric
5	chol	Serum Cholesterol in mg/dl [	Numeric
6	fbs	fasting blood sugar- 1: if >120 mg/dl, 0: if <120 mg/dl	Nominal
7	restecg	Rest Electrocardiographic Results [0 to 2]	Nominal
8	thalach	Maximum Heart Rate obtained [71 to 202]	Numeric
9	exang	exercise with angina [Yes-1, No-0]	Nominal
10	oldpeak	ST depression introduced through exercise [0 to 2]6	Numeric
11	slope	slope of the ST segment [0 to 2]	Nominal
12	thal	Status of the heart described by 4 level	Nominal
13	ca	Number of major vessels ranging from 0 - 4	Numeric
14	target	Heart disease diagnosis 1 or 0	Nominal

For this research, we used the Cleveland CVD Dataset, which is accessible online via the UCI Repository. The collection consists of 303 patient records in total. The missing values in the dataset are handled by statistical data preparation. Class Values 1 and 0 represent "tested negative for the disease" and "tried positive for the disease," respectively. The dataset should be handled cautiously though, as there are a lot of outliers in it. A variety of charting methods were used to analyze the distribution of the data and find any anomalies. Performing all of these pre-processing techniques is essential prior to using the data for classification or prediction. A technique for converting categorical data into a format that ML classifiers may employ to produce more precise predictions is one hot encoding.

We so employed a single hot encoding for our implementation. MinMaxScaler subtracts the minimum value of the feature from each value and then divides by the range. The ranges are defined as the differences between the original maximum and minimum. The form of the original distribution is preserved by MinMaxScaler. MinMaxScaler was the tool we used for normalisation.

Data Balancing

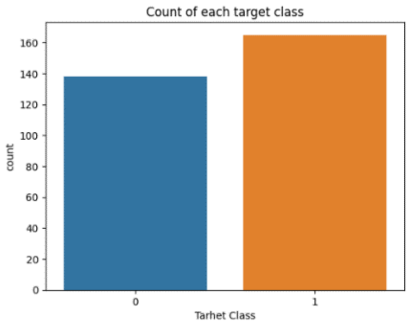

Figure 1: Target class view

Data balancing is required for reliable findings since the data balance graph indicates that the two target classes are equal. A patient with heart illness is represented by the number "0" in Figure 1, whereas a patient without cardiovascular disease is represented by the number "1".

Kernal Distribution Estimation (KDE)

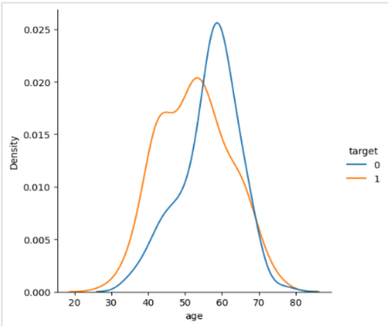

Figure 2: Kernal Distribution Estimation (KDE)

The figure 2 displays a curve chart representing the probability density functions calculated by KDE for the patient and control samples in the dataset with a 1:1 matching ratio. It is evident from looking at Figure 2's content that the probability density functions of the control and sick samples differed significantly. Put differently, in diagnostic records that were employed as defining characteristics, they showed radically divergent data distributions. The x axis showing the age and y showing density.

Sex Distribution

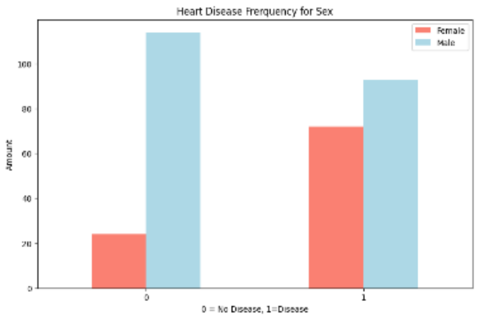

Figure 3: Sex distribution of data

Figure 3 shows how the data is fairly balanced by looking at the plot. Among the data set's many attributes is the sex attribute, which has a value of 0 for females and 1 for men. We might also make use of countplot. This makes the around 2:1 male to female ratio quite clear.

Statistical of feature

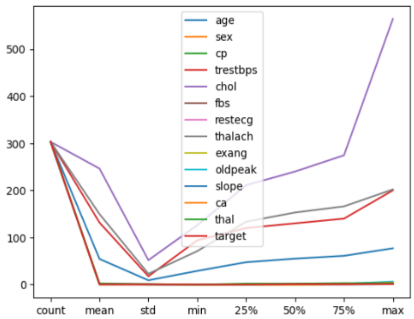

Figure 4: Statistical of feature

Conferring to the figure 4, there are 14 features are shown. Age, restecg, sex, trestbps, cp, fbs, chol, thalach, exang, oldpeak, slope, ca, thal and target are the features of the dataset. Chol has the maximimum value.

Correlation Metrics

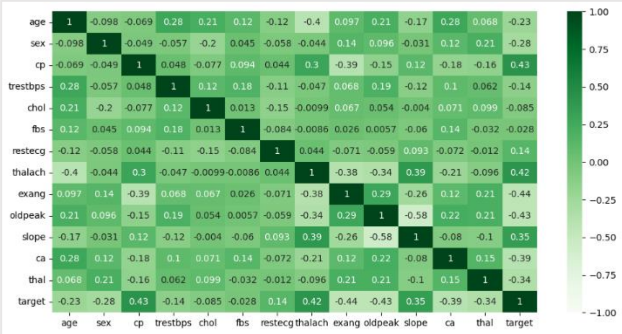

Figure 5: Heat map

The correlation matrix related to the dataset on heart disease is shown in Figure 5. The correlation matrix shows that cardiac disease has the most negative associated with exang (correlation = −0.44) and the largest positive link with cp (correlation = 0.43). With a correlation of −0.58, oldpeak and slope likewise have a very strong relationship. Utilising our correlation table, create a comparable comparison for the red text below.

Heart rate tends to drop with age, as Fig. 4 illustrates. Based on the matrix, the results show a poor association between the numerical characteristics and the target variable. Heart disease and Oldpeak, a depression-related number, have a favourable correlation. The maximum heart rate and cardiac disease are inversely associated. An intriguing negative correlation has been found between heart disease and cholesterol.

Modelling

A training dataset (80%) and a testing dataset (20%) make up the dataset. Taking into account that a model is trained using the training dataset, and its performance is evaluated using the testing dataset. Then, the accuracy, precision, recall, and F-measure are used to evaluate the performance of each classifier.

Artificial Neural Network (ANN)

A computational model called an Artificial Neural Network (ANN) is based on the neural architecture of the human brain. It is made up of layers of networked nodes, or neurons. These nodes process information, and during training, the network modifies the connection strengths (weights) to learn from the input. This permits the network to identify patterns, anticipate outcomes, and perform a variety of machine learning and artificial intelligence tasks.

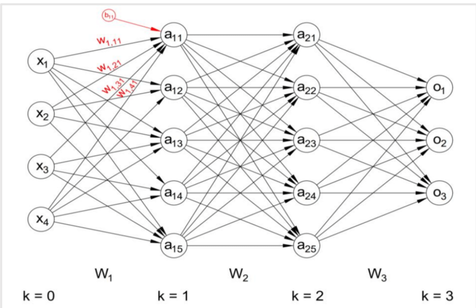

Figure 6: Statistical of feature

$$z = f(x.w) = f\left(\sum_{i=1}^{n} xw\right) \qquad (1)$$

Convolutional Nueral Network (CNN)

The CNNs, are a subclass of neural networks that are mainly noble at processing input with a topology imminent a grid, such as images. A binary representation of visual data is what makes up a digital picture. It is made up of a grid-like preparation of pixels with pixel values to designate the colour as well as glare of all pixel.

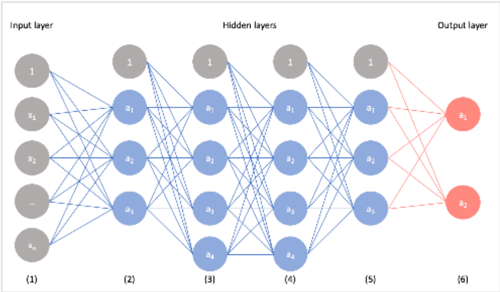

Figure 7: Architecture of a CNN

Long Short-Term Memory (LSTM)

A prevalent Recurrent Neural Network (RNN) architecture in DL is called LSTM (Long Short-Term Memory). It is excellent at identifying long-term dependencies, which makes sequence prediction jobs a perfect fit for it.

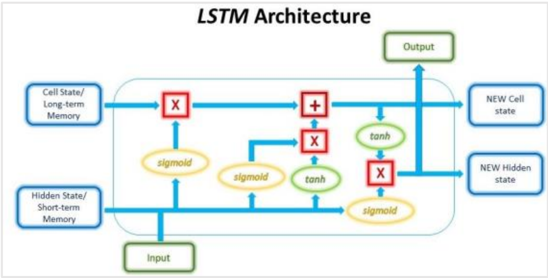

Figure 8: Architecture of a LSTM

Because LSTM has feedback connections, as opposed to standard neural networks, it can grip whole data orders as opposed to simply single data points. Because of this, it is very good at classifying and predicting patterns in sequential data, such as time series, voice, and text. By evaluating the hyperplane that lengthens the border line separating the classes in the training set, support vector machines (SVM) classify data [19]. The formula for a hyperplane is as follows:

Architecture of Predicted System

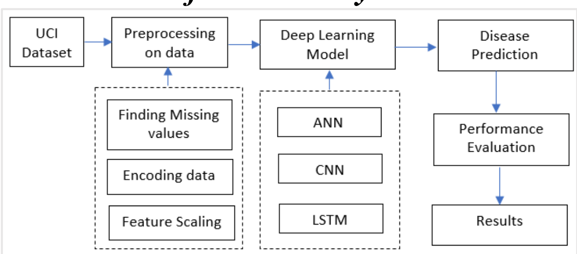

Figure 9: Architecture of predicted system

Performances Parameters

Accuracy, specificity, sensitivity and area under the receiver operating characteristic curve (AUC) were the matrices obtained while training on the training dataset and fitting the models to the test dataset to see which performed better. For every model, we calculate the confusion matrix, as indicated in Table 2.

The accuracy, recall, precision, and F-measure are among the characteristics used to assess the prediction model's performance. The accuracy, precision, recall, and F-measure are among the characteristics used to assess the prediction model's performance.

Table 2: Confusion metrics

	Actual positive	**Actual Negative**
Positive	TP	FP
Negative	FN	TN

Training data include eighty percent of the data set, while testing data make up the remaining twenty percent. Once the data has been prepared, the procedures are applied to find the confusion matrix. An assessment of the accuracy of the methodology has been made. Accuracy has been assessed using a confusion matrix.

The algorithms' performance will be compared using Equation's CAD prediction accuracy as a benchmark. This approach will increase the models' accuracy with each fold, giving each model 10 accuracies at the end of training. The accuracy average will be computed in addition to the accuracy standard deviation.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \qquad (2)$$

Conversely, recall is dogged by separating the total number of samples that tested positive by the number of positive results that really occurred. The goal of recall is to ascertain what proportion of accurate positive predictions were really made. Below is the formula.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (3)$$

By dividing the total number of positive outcomes that a classifier predicts by the total number of true positives, the accuracy is computed. In short, accuracy is to ascertain the fraction of all positive forecasts that were, in fact, accurate. The following formula is displayed.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (4)$$

The F-score is a metric that is determined by taking into account both the test's accuracy and recall. In this essay, it is defined as the harmonic mean of recall and accuracy. The following is the formula for the F-score, commonly referred to as the F1 score or the F-measure.

$$\text{F1 Score} = \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision+Recall})} \qquad (5)$$

Results and Discussion

Table 3: Accuracy of each models

Model	Accuracy
ANN	0.901
CNN	0.885
LSTM	0.918

The accuracy of the DL classifier is provided in the above table. CNN measures, in particular, exhibit worse accuracy than the remaining metrics. The CNN has an 88% accuracy rate. Subsequently, ANN achieved 90% accuracy. Next, LSTM achieved 91% of accuracy. The suggested LSTM model achieves the highest accuracy when compared to DL models.

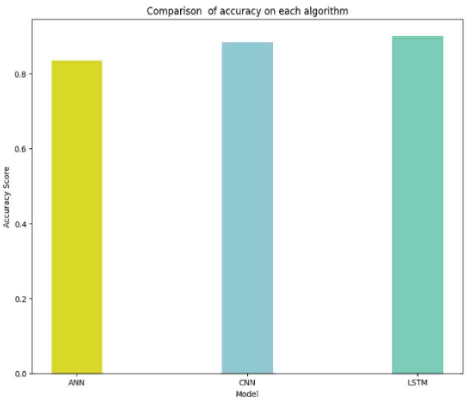

Figure 10: Comparision of accuracy of each algorithm

The graph up above compares the accuracy of the different methods. At least 88% accuracy is achieved by all algorithms. 90% of the time, the ANN is accurate. CNN then attained an accuracy of 88%. Next, LSTM reached 91%. In summary, LSTM attained the highest accuracy rate of 91%. Among the DL models, the proposed LSTM model has the best accuracy.

Table 4: F1-score, recall and precision of each models

Model	Precision	Recall	F1 Score
ANN	0.888	0.831	0.884
CNN	0.865	0.911	0.898
LSTM	0.919	0.931	0.925

Table IV shows that the precision, recall, and F1-score of the DL classifiers are smaller than the performance metrics of the innovative technique. ANN in particular has 83% recall, 88% F1 score, and 88% precision. Next, CNN obtained 89% of F1-score, 91 % of recall, and 86% of precision. 93% of recall, 92% of F1-score, and 91% of precision. When DL classifiers were compared, ANN and CNN performed worse than the LSTM classifier. Regarding the peak performance that LSTM achieved. An average of 92% is found. Thus, it can be concluded that LSTM performs the best when it comes to CVD.

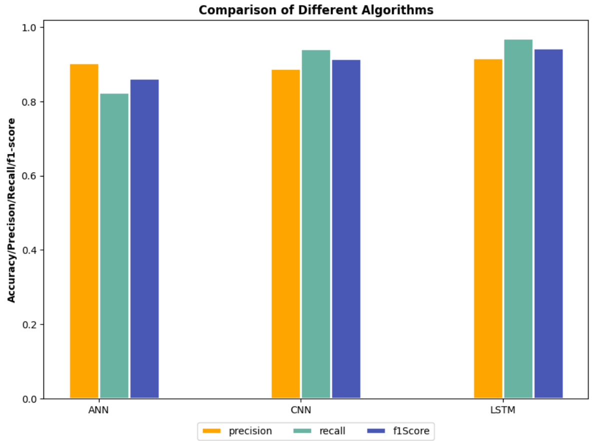

Figure 11: F1-score, recall and precision of each models

Figure 9 shows that when DL classifiers were compared side by side, ANN and CNN fared poorly. About the highest level of performance that LSTM attained. 92% on average is discovered. Consequently, it may be said that LSTM has the best CVD performance.

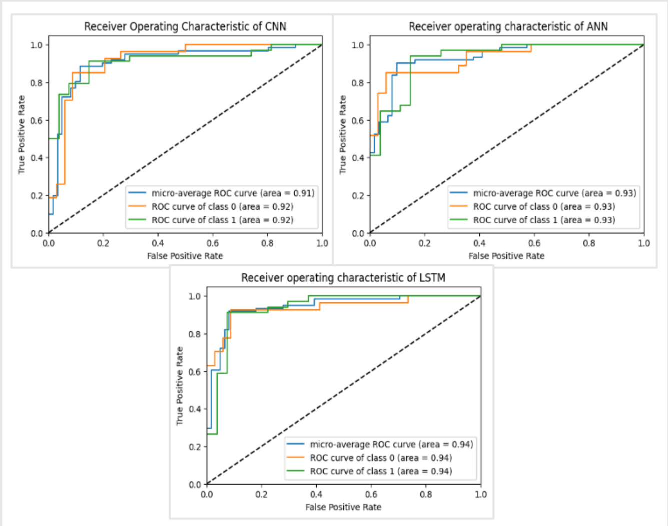

Figure 12: ROC of each algorithms

We employed many models. The most accurate models are used in the voting process, and the resulting accuracies of the models are shown in Table IV. Additional techniques were created and evaluated by merging these algorithms, as indicated in Figure 10 and described in Table IV. We assessed the algorithms' performance by looking at their recall, accuracy, precision, and F1-score. When compared to the other classifiers, the LSTM classifier has the highest classification accuracy (92%). Figure 10's computed and shown ROC curves demonstrate the classifier's diagnosing capability. The closer the ROC curve area value is to one, the better the model performs in terms of diagnosis.

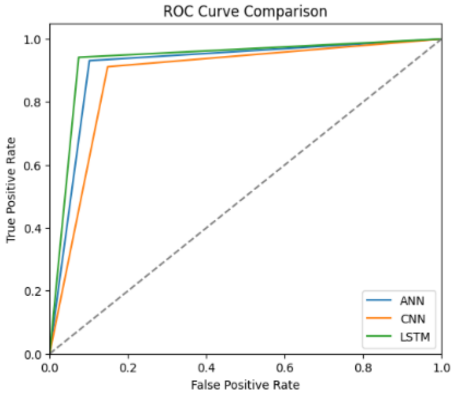

Figure 13: ROC of all algorithms

The created model is compared with other reported models that used deep learning to predict CVD. Accuracy is utilised as a performance parameter to evaluate the created model against previous studies. The accuracy of each performance matrix utilised in the experiment was displayed using ROC curves. Considering all factors, the LSTM classifier achieves the highest performance, receiving 92% of the possible points for F1-score, accuracy, recall, and precision. The graph below shows how different algorithms compare in terms of accuracy. Each algorithm has a minimum 88% accuracy rate. This suggests that ANN and CNN have the lowest accuracy when compared to other algorithms. Overall, these algorithms were successful 88% of the time. The best LSTM model has an accuracy rate of 92% when accuracy is taken into account.

Conclusion

Because CVD has a high death rate globally, it has become a major health issue for many people. By methodically assessing clinical data, heart attacks, coronary artery diseases, and other cardiovascular problems can be recognised; early diagnosis of heart sickness has the potential to save many lives. Many people are aware of CVD's high death rate. Early and accurate identification of cardiovascular disorders in humans can significantly improve the patient's prognosis by slowing the course of heart failure. Over time, plaque builds up and partially obstructs blood flow in the coronary arteries, mostly consisting of calcium, fibrin, and cholesterol. This contributes to the development of CVD.

The major objective of this research is to provide a novel approach that uses DL algorithms to increase the accuracy of CVD prediction in a categorization environment. This paper summarizes the accuracy scores of CNN, ANN, and LSTM algorithms for heart condition prediction using the UCI dataset. With an accuracy score of 91%, the LSTM algorithm is the most successful in predicting CVD, per the study's findings.

References

A. Cüvitoğlu and Z. Işik, “Classification of CAD dataset by using principal component analysis and machine learning approaches,” *2018 5th International Conference on Electrical and Electronics Engineering, ICEEE 2018*, pp. 340–343, 2018.

J. I. Zong Chen and H. P, “Early Prediction of Coronary Artery Disease (CAD) by Machine Learning Method - A Comparative Study,” *Journal of Artificial Intelligence and Capsule Networks*, vol. 3, no. 1, pp. 17–33, 2021.

A. Gupta, R. Kumar, H. S. Arora, and B. Raman, “C-CADZ: computational intelligence system for coronary artery disease detection using Z-Alizadeh Sani dataset,” *Applied Intelligence*, vol. 52, no. 3, pp. 2436–2464, 2022.

A. R. M. Nizzad *et al.*, “Internet of Things Based Automatic System for the Traffic Violation,” in *2021 5th International Conference on Electrical, Electronics, Communication, Computer*

Technologies and Optimization Techniques, ICEECCOT 2021 - Proceedings, 2021, no. December, pp. 371–376.

S. Bhattacharya, O. Mazumder, D. Roy, A. Sinha, and A. Ghose, "Synthetic data generation through statistical explosion: Improving classification accuracy of coronary artery disease using PPG," *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, vol. 2020-May, pp. 1165–1169, 2020.

M. Gada, K. Damania, and S. Sankhe, "Cyberbullying Detection using LSTM-CNN architecture and its applications," 2021.

R. Ganesh Babu, P. Karthika, and K. Elangovan, "Performance Analysis for Image Security using SVM and ANN Classification Techniques," *Proceedings of the 3rd International Conference on Electronics and Communication and Aerospace Technology, ICECA 2019*, pp. 460–465, 2019.

R. Ri-, "Combate Automático às Fake News nos Meios Di- gitais," pp. 5–40.

K. R. Dahal and Y. Gautam, "Argumentative Comparative Analysis of Machine Learning on Coronary Artery Disease," *Open Journal of Statistics*, vol. 10, no. 04, pp. 694–705, 2020.

I. D. Apostolopoulos and B. A. Tzani, "Towards an Internet of Things application for the prognosis of Coronary Artery Disease using Machine Learning and Fuzzy Logic," *13th International Conference on Information, Intelligence, Systems and Applications, IISA 2022*, pp. 6–9, 2022.

U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan, and C. K. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," *Knowledge-Based Systems*, vol. 132, pp. 62–71, 2017.

L. J. Muhammad, I. Al-Shourbaji, A. A. Haruna, I. A. Mohammed, A. Ahmad, and M. B. Jibrin, "Machine Learning Predictive Models for Coronary Artery Disease," *SN Computer Science*, vol. 2, no. 5, 2021.

S. S. Alotaibi *et al.*, "Automated prediction of coronary artery disease using random forest and naïve bayes," *2020 International Conference on Advanced Computer Science and Information Systems, ICACSIS 2020*, no. Cvd, pp. 109–114, 2020.

A. Ratnayake, M. R. Ine, and R. Drewello, "Preservation of Archeological Sites Using 3D-Scanning Documentation Case Study: Sri Dalada Maligawa, Kandy, Sri Lanka," *2018 National Information Technology Conference, NITC 2018*, pp. 2–4, 2018.

A. Akella and S. Akella, "Machine learning algorithms for predicting coronary artery disease: Efforts toward an open source solution," *Future Science OA*, vol. 7, no. 6, 2021.

M. Shamsollahi, A. Badiee, and M. Ghazanfari, "Using Combined Descriptive and Predictive Methods of Data Mining for Coronary Artery Disease Prediction: a Case Study Approach," *Journal of AI and Data Mining*, vol. 7, no. 1, pp. 47–58, 2019.

A. H. Shahid, M. P. Singh, B. Roy, and A. Aadarsh, "Coronary artery disease diagnosis using feature selection based hybrid extreme learning machine," *Proceedings - 3rd International Conference on Information and Computer Technologies, ICICT 2020*, pp. 341–346, 2020.

K. S. Nugroho, A. Y. Sukmadewa, A. Vidianto, and W. F. Mahmudy, "Effective predictive modelling for coronary artery diseases using support vector machine," *IAES International Journal of Artificial Intelligence*, vol. 11, no. 1, pp. 345–355, 2022.

D. Zhang, "Pingyao Historic City and Qiao Family Courtyard Conference Abstract."

H. Feng and J. Shao, "Facial Expression Recognition Based on Local Features of Transfer Learning," *Proceedings of 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference, ITNEC 2020*, no. Itnec, pp. 71–76, 2020.

P. Arulanthu and E. Perumal, "An intelligent IoT with cloud centric medical decision support system for chronic kidney disease prediction," *International Journal of Imaging Systems and Technology*, vol. 30, no. 3, pp. 815–827, 2020.

J. I. Gallego-Gómez *et al.*, "The COVID-19 pandemic and its impact on homebound nursing students," *International Journal of Environmental Research and Public Health*, vol. 17, no. 20, pp. 1–10, 2020.

Savita, G. Rani, and A. Mittal, "An Optimized Machine Learning Approach for Coronary Artery Disease Detection," *Journal of Advances in Information Technology*, vol. 14, no. 1, 66–76, 2023.

B. Nazlı, G. Yasemin, and H. Altural, "Classification of Coronary Artery Disease Using Different Machine Learning Algorithms," *International Journal of Education and Management Engineering*, vol. 10, no. 4, pp. 1–7, 2020.

A. Caliskan and M. E. Yuksel, "Classification of coronary artery disease data sets by using a deep neural network," *The EuroBiotech Journal*, vol. 1, no. 4, pp. 271–277, 2017.

K. AKYOL, "Feature Selection Based Data Mining Approach for Coronary Artery Disease Diagnosis," *Academic Platform Journal of Engineering and Science*, 9, no. 3, 451–459, 2021.

R. Alizadehsani, M. J. Hosseini, Z. A. Sani, A. Ghandeharioun, and R. Boghrati, "Diagnosis of coronary artery disease using cost-sensitive algorithms," *Proceedings - 12th IEEE International Conference on Data Mining Workshops, ICDMW 2012*, no. December, pp. 9–16, 2012.

A. Maach, J. Elalami, N. Elalami, and E. H. El Mazoudi, "An Intelligent Decision Support Ensemble Voting Model for Coronary Artery Disease Prediction in Smart Healthcare Monitoring Environments," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 9, pp. 711–724, 2022.

S. Smys, A. Basar, and H. Wang, "Artificial Neural Network Based Power Management for Smart Street Lighting Systems," *Journal of Artificial intelligence and Capsule Networks*, vol. 02, no. 01, pp. 42–52, 2020.

M. Hartmann, U. S. Hashmi, and A. Imran, "Edge computing in smart health care systems: Review, challenges, and research directions," *Transactions on Emerging Telecommunications Technologies*, no. December 2018, pp. 1–25, 2019.

I. Mukti and Y. Prambudia, "Challenges in Governing the Digital Transportation Ecosystem in Jakarta: A Research Direction in Smart City Frameworks," *Challenges*, vol. 9, no. 1, p. 14, 2018.

Z. Zulkefli and M. Mahinderjit Singh, "Sentient-based Access Control model: A mitigation technique for Advanced Persistent Threats in Smartphones," *Journal of Information Security and Applications*, vol. 51, p. 102431, 2020.

M. G. M. Barbade, M. M. V. Ganesh, M. P. S. Shivraj, and M. S. S. Bharat, "Automatic Sprinkler System using Arduino," *Indian Journal of Microprocessors and Microcontroller*, vol. 1, no. 2, pp. 12–16, 2021.

S. Kamoji, D. Koshti, J. Noronha, E. Arulraj, and E. Clement, "Deep Learning-based Smart Street Lamps – A Solution to Urban Pollution," in *Second International Conference on Inventive Research in Computing Applications (ICIRCA-2020)*, 2020, pp. 478–482.

M. Pike, N. M. Mustafa, D. Towey, and V. Brusic, "Sensor networks and data management in healthcare: Emerging technologies and new challenges," *Proceedings - International Computer Software and Applications Conference*, vol. 1, pp. 834–839, 2019.

J. Wan *et al.*, "Wearable IoT enabled real-time health monitoring system," *Eurasip Journal on Wireless Communications and Networking*, vol. 2018, no. 1, 2018.

P. K. Illa and N. Padhi, "Practical Guide to Smart Factory Transition Using IoT, Big Data and Edge Analytics," *IEEE Access*, vol. 6, no. c, pp. 55162–55170, 2018.

A. N. Repaka, S. D. Ravikanti, and R. G. Franklin, "Design and implementing heart disease prediction using naives Bayesian," *Proceedings of the International Conference on Trends in Electronics and Informatics, ICOEI 2019*, vol. 2019-April, no. Icoei, pp. 292–297, 2019.

S. A. Asra, "Various Technologies used in Smart Transportation System in the Direction of a Smart City : A Systematic Review," 2022.

S. A. Asra, "Artificial Intelligence (AI) in Augmented Reality (AR), Virtual Reality (VR) and Mixed Reality (MR) Experiences : Enhancing Immersion and Interaction for User Experiences," 2022.