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Cardiovascular (Heart) Diseases Prediction using Deep Learning Neural Network Model

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Abstract

Deep learning plays an important role in the field of medical science in solving health issues and diagnosing various diseases. So in this paper, we will discuss cardiovascular disease. We proposed a model for cardiovascular disease prediction. Cardiovascular disease is a key area where a deep neural network can be used, so we can improve the overall quality of the classification of cardiovascular disease. The classification can be performed in various ways, like KNN, SVM, Naïve Bayes, and Random Forest. The Cardiovascular Disease UCI dataset was used to demonstrate that Talos hyper-parameter optimization is more efficient than others.

1.0. Introduction

In our day to day life, today generation is very busy in our daily routine schedule which feels to nervousness, restlessness and stress. Each individual have distinctive pulse rate and blood pressure which ranges from 60 to 100 BPM for pulse rate and 120/80 to 140/90 for blood pressure. In worldwide, heart disease is the major issue in human life. Heart means “Cardio”. Heart disease category is called Cardiologist disease. The different types of heart disease are following: Congenital heart disease, Arrhythmia, Coronary artery disease, Dilated cardiomyopathy, Myocardial infarction, Heart failure, Hypertrophic cardiomyopathy, and Mitral regurgitation.

Deep learning is a more popular machine learning method. It is not only when applying it in image classification tasks but also uses normal tabular data. In this model, we create a deep learning neural network model using Talos. Talos is a hyperparameter optimization techniques. In this model, we can use the Talos optimizer with Keras library. Keras is a deep learning neural network library. Keras creates a high-level neural networks model. It developed for easy and fast experimentation. Keras supports both convolutional neural networks (CNN) and recurrent neural networks (RNN), as well as combinations of the two. It runs perfectly on CPU and GPU. Talos is a fully automated POD (Prepare, Optimize, Deploy) pipeline that stability yields state by step prediction results in a wide range of prediction related problems.
These are some of the specific hyperparameters and search ranges optimized mentioned using Talos for the cardiovascular disease prediction.

Learning Rate:

Range: [0.0001, 0.01]

The learning rate determines the step size during gradient descent optimization. A low learning rate can result in slow convergence, while a high learning rate may cause divergence or overshooting.

Batch Size:

Range: [16, 128]

The batch size specifies the number of samples processed in each iteration of training. Larger batch sizes can accelerate training but may lead to increased memory usage and computational overhead.

Number of Layers

Range: [2, 6]

The number of layers in the neural network architecture. Increasing the number of layers can enable the model to learn complex representations but may also increase the risk of overfitting.

Number of Neurons per Layer

Range: [32, 512]

The number of neurons or units in each hidden layer. A higher number of neurons can increase the model's capacity to capture intricate patterns but may also lead to overfitting if not regularized properly.

Activation Functions

Options: ['relu', 'sigmoid', 'tanh']

The activation function applied to the output of each neuron in the hidden layers. Different activation functions introduce non-linearities into the model, influencing its expressive power and gradient flow during training.

Dropout Rate

Range: [0.1, 0.5]

Dropout is a regularization technique that randomly deactivates a fraction of neurons during training to prevent overfitting. The dropout rate determines the probability of neuron deactivation.

Optimizer

Options: ['adam', 'sgd', 'rmsprop']

The optimization algorithm used to update the model parameters during training. Adam, SGD (Stochastic Gradient Descent), and RMSprop are popular choices, each with its own advantages and drawbacks.

Weight Initialization

Options: ['glorot_uniform', 'he_normal']

The method used to initialize the weights of the neural network layers. Proper weight initialization can facilitate training convergence and prevent vanishing or exploding gradients.
In this field, large number of researches has been done by using various algorithms and techniques. This paper aim to achieve better accuracy and to make the system more efficient so that it can predict the chances of a heart attack.

Nowadays many researchers used machine learning, deep learning and data mining in healthcare to predict diseases but each research gives their opinion and prediction accuracy according to your research.

[1] suggested a hybrid method using two machine learning algorithms, one is SVM (Support Vector Machine) and another is GA (Genetic Algorithm), both are effectively combined with in this approach. Data mining tools like LIBSVM and WEKA are used for this analysis here we collected

5 different dataset from the IUC repository. When we applied the hybrid model it reaches to an accuracy of 84.07% for heart disease, 78.26 for diabetics and 76.20% for breast cancer and 86.12% for Hepatitis

[2] recommended data mining perspectives to detected heart diseases in human body. In this data mining approaches, WEKA tool is used for machine learning purposes which is used multiple algorithms for data mining like - J48, Naïve bayes and bagging. The UCI laboratory is a part of machine learning. In the heart disease dataset 313 attributes and 13 attributes for prediction. Naïve Bayes gives 82.31% accuracy, J48 offers 84.35% and Bagging offers 85.35% accuracy in classification.

As suggested by [3] using the Naive Bayes algorithm which uses Bayes approach. Naïve Bayes algorithm has a robust principle of independence dataset. Here we use one of the leading diabetes research dataset which consist of 500 patients. WEKA tools are data mining tools and perform classification using 70% for training and 30% for testing dataset. Accuracy of Naive Bayes 86.419%.

[4] analyses the existing works on heart disease prediction which uses data mining. The data mining techniques are commonly used in heart disease prediction. They also discuss the databases used such as the heart disease data set from UCI repository, tools used such as Weka, Rapid Miner, Data melt, Apache Mahout, Rattle, KEEL, R data mining and soon. They conclude that the use of single algorithm results in better accuracy in prediction. But the use of hybridization of two or more algorithms can enhance and improve the heart disease prediction with good accuracy.

[6] maintaining 10 methods, it's using heart disease UCI repository in the 4 sets, and found that a Partial Least Square Discriminant Analysis (PLS-DA) method accuracy of 86.13%.

[7] as suggested to enhanced the prediction of heart diseases dataset using the data techniques. SVM provided the better and efficient accuracy 85%. In SVM, parallel fashion gives better accuracy than sequential SVM.

[9] Different Data Mining Approaches for Predicting Heart Disease. WEKA tool, MATLAB. Accuracy of Neural Network 84% and Accuracy of Hybrid Systems 89%.

[10] as suggested to Prediction and Analysis for Heart Diseases using data mining techniques. J48, Naïve Bayes (NB), Support Vector Machine (SVM). It gives the better result which helps to improve the quality of services and reduce the cost to individuals.

Extensive research has been conducted in this domain employing a variety of algorithms and techniques. This paper introduces a methodology utilizing a Deep Learning Neural Network Model for predicting Cardiovascular (heart) disease. The approach incorporates the Talos optimizer within the Keras library, known for its high-level neural network modeling capabilities. Keras accommodates convolutional neural networks (CNN) and recurrent neural networks (RNN), as well as hybrid architectures, operating seamlessly on both CPU and GPU platforms.

2.0. Methodology

In this paper, we deploy a model "Optimized DNN using Talos" and compare the method to others it is more efficient to others. This model provided a high accuracy compared to others.

Deep Neural Networks (DNNs) have revolutionized various fields by providing powerful tools for data analysis, pattern recognition, and prediction tasks. In the realm of healthcare, DNNs have shown promising results in predicting diseases, including cardiovascular diseases (CVDs). This essay delves into a methodology centered around optimizing DNNs using Talos, a hyperparameter optimization library, focusing on neural network architecture, hyperparameter tuning process, and evaluation metrics in the context of predicting CVDs.

The architecture of a neural network plays a pivotal role in its performance. For predicting CVDs, a DNN architecture is designed with multiple layers, including input, hidden, and output layers. The input layer represents the features extracted from patient data, such as age, blood pressure, cholesterol levels, and more. Hidden layers, consisting of densely connected neurons, extract intricate patterns from the input data. The output layer provides the prediction regarding the likelihood of a patient developing a cardiovascular condition. The architecture can be further enhanced with techniques like dropout regularization to prevent overfitting and batch normalization for faster convergence.

Optimizing hyperparameters is crucial for improving the performance and generalization of DNN models. Talos simplifies this process by providing a systematic approach to explore various hyperparameter configurations efficiently. The tuning process typically involves parameters such as learning rate, batch size, activation functions, number of layers, and neurons per layer. Talos employs techniques like random search, grid search, or Bayesian optimization to traverse the hyperparameter space and identify the optimal configuration. This iterative process aims to maximize the model's performance metrics while minimizing overfitting.

Evaluation metrics are essential for assessing the efficacy of the predictive model. In the context of CVD prediction, common evaluation metrics include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Accuracy measures the overall correctness of predictions, while precision quantifies the proportion of true positive predictions among all positive predictions. Recall, also known as sensitivity, measures the proportion of true positives correctly identified by the model. F1-score balances precision and recall, providing a harmonic mean between the two. AUC-ROC evaluates the model's ability to discriminate between positive and negative instances across various thresholds. These metrics collectively offer insights into the model's performance and help in fine-tuning the predictive algorithm.

The methodology of optimizing DNNs using Talos presents a comprehensive approach to building robust predictive models for cardiovascular disease prediction. By carefully designing neural network architectures, leveraging hyperparameter tuning techniques, and evaluating performance using appropriate metrics, researchers and practitioners can develop accurate and reliable models to aid in early detection and prevention of CVDs. This methodology not only enhances the predictive capabilities of DNNs but also contributes to advancing the field of healthcare analytics and personalized medicine.

In this model, we are following some steps.

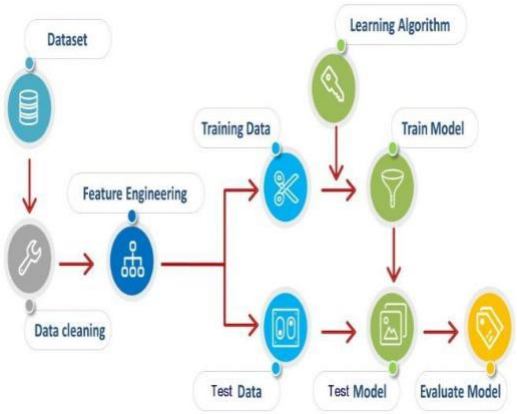


Fig.1- Flow diagram

A. Dataset: - In this paper, we are using the Heart Diseases datasets. In Heart Diseases, 14 attributes are given shown in fig.2 and 303 columns that represent the patient's data. In this database, we apply the DNN using Talos and predict the diseases
B. Data cleaning: - Data cleaning is the first and necessary step for any project processes and data models. It means filtering and modifying your data such that it is easier to explore and understand.

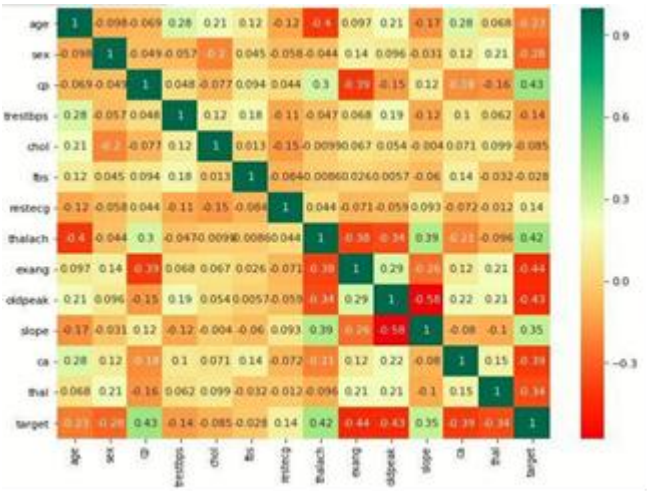


Fig.2- Heat-map

C. Feature engineering: - Features engineering is the most popular part of the deep learning. Features engineering is used for extracting some features data set. Features engineering is the process of transferring the raw data to features data and this features data improve the quality of the model and provide better accuracy.
D. Learning algorithms:- We are using the many types of learning algorithms –

a) Logistic regression: - Logistic regression is a classification algorithm for categorical variables. Sigmoid function is the most part of logistic regression.

Algorithms: - Logistic regression algo. following some steps.

1. Initialize Θ.
2. Calculate Y = σ(ΘTX) for a customer.
3. Compare the output of Y with actual output of customer y, record it as error.
4. Calculate the cost of all customers.
5. Change the Θ to reduce the cost.
6. Go To Step 2.
7. Stop

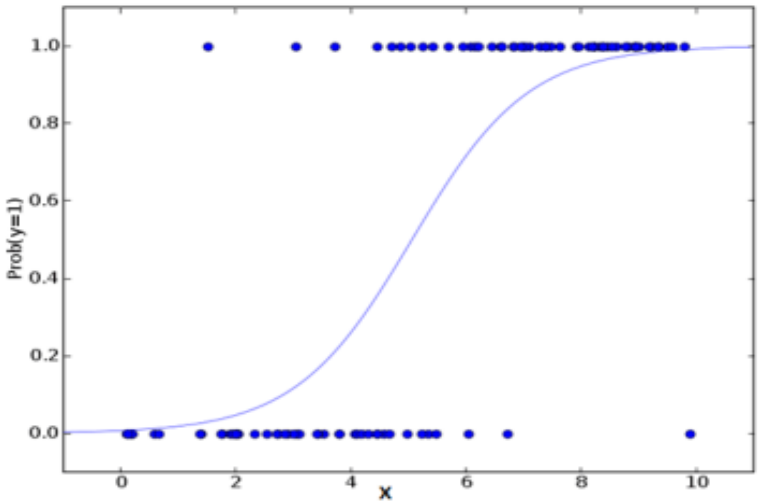


Fig.3- Logistic regression

b) K-NN: - KNN is a non- parametric machine learning algorithm. It is a supervised learning algorithm. It means to predict the output from the input data.

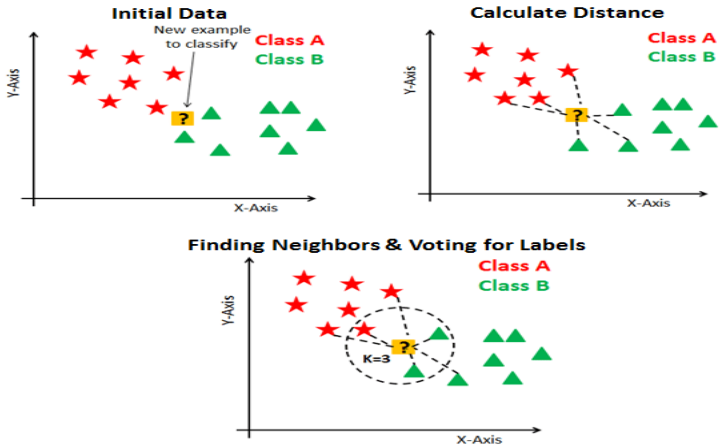


Fig.4- KNN

K-NN Algorithms: - K-NN algo follows some steps.

1. Pick a value for K.
2. Calculate the distance of unknown case from all cases.
3. Select the K- observations in the training data that nearest to the unknown data point.
4. Predict the response of unknown data point using the most popular response value from the KNN
5. Stop.

In this algorithms data is divided into training and test data sets. The training dataset is used for model building and training. K- value is decided which is often the square root of the number of observations. Now the test data is predicated on the model built.

c) Support Vector Machine (SVM):- SVM is supervised deep learning algorithm which can be used both classification and regression.

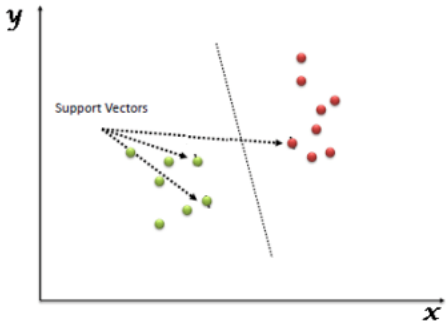


Fig.5- Support vector

The SVM algorithm is used to predict this disease by plotting the training dataset where a hyperplane classifies in two – presence and absence of heart disease.

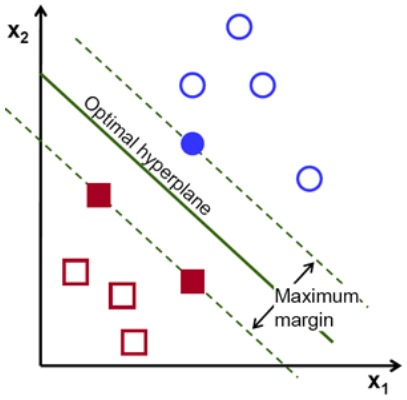


Fig.6- SVM

SVM is used to handle class imbalance. Class imbalance is a problem in machine learning when the total number of positive and negative is not the same and the classifier will not perform well

d) Naïve Bayes: - Naive Bayes is a probabilistic machine learning classification algorithm based on the Bayes Theorem. It is used in a wide variety of classification tasks.

Bayes Rule is a way of going from P(X|Y), known from the training dataset, to find P(Y|X), known from the test data.

$$\rho(X|Y) = \frac{\rho(X \cap Y)}{\rho(Y)} \quad \rho(Y|X) = \frac{\rho(Y \cap X)}{\rho(X)} \tag{1}$$

P (X|Y) is known data means P (Evidence Outcome) for testing and P (Y|X) is unknown data means P (Outcome Evidence) for testing.

$$\rho(Y|X) = \frac{\rho(X|Y) * \rho(Y)}{\rho(X)} \tag{2}$$

e) Hyper-parameter optimization (Talos):- Talos follows POD (Prepare, optimize, Deploy), process workflow and additional functionality for evaluation, reporting, including plots for visual analysis.

Prepare (P): - this is the first process for preparation of defining the hyperparameter space for the experiments and it is the setting oof experiment options such as choosing for the optimization strategy.

Optimize (O): - This is the second process for optimization. It's automated process of finding an optimal hyperparameter combination for a well generalizing model for a given prediction task.
Deploy (D): - This is the third process for deployment. It's automated the process of sorting locally the required assets for local and remote deployment of a model for production purpose.
Reporting and evaluation are the last process after all 3 POD workflow. It provides several facilities for analysis and evaluation of experiments, including the all plots for epoch-by-epoch visual analysis for experimental progress.
f) Random forest classifier: - Random Forest classifier makes a set of decision trees from randomly selected subset of training dataset. It aggregates the votes from different decision trees to decide the final class of the test object.

Random Forest Algorithms: - This algo follows some steps.
1. Choose an attributes from your dataset.
2. Calculate the significance of attribute in splitting of data.
3. Split data based on the value of the best attribute.
4. Go to Step 1.
E. Train & Test model:-Data is split into test and train dataset where the train set contains a output field on which the model learns.

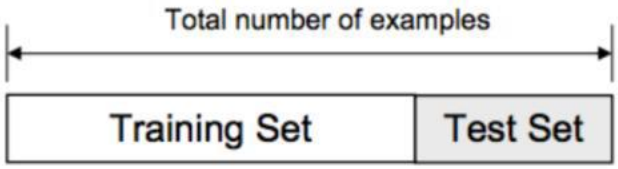
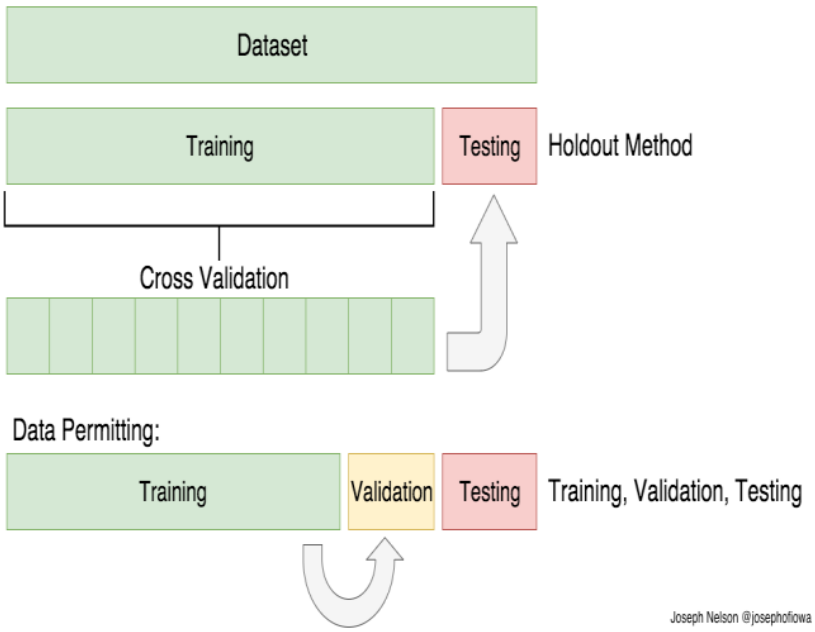


Fig.7- Data splitting

Here we applied cross-validation so our data remains randomly across the train set.



In the training/testing model, two words are very popular first is Under-fitting and second is Over-fitting.
If the model is under-fitting, then our model does not fill well and perform poorly. And if it Over-fits then it performs poorly on test set.

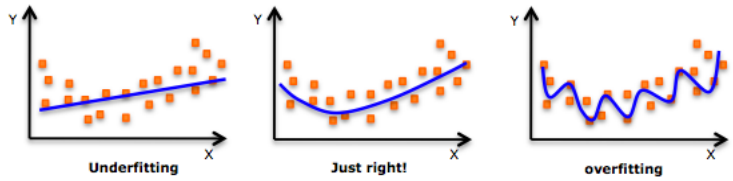


Fig.9 –Under-fitting and over-fitting

F. Evaluate model:-We deploy the neural networks model. In this model, we are using the input layer, output layer, hidden layer, and activation function. In this model, we deploy the deep neural network model using Talos optimization. The purpose of Talos optimization is allowing to use to continue working with Keras models.

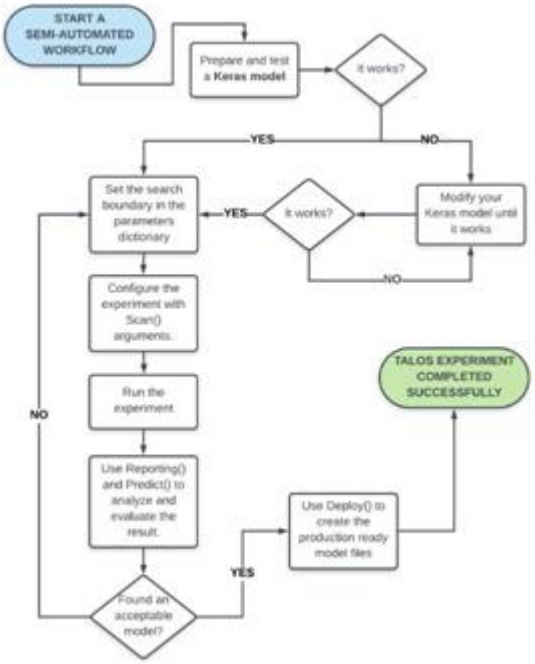


Fig.10- Hyper-parameter optimization technique using Talos

3.0. Results

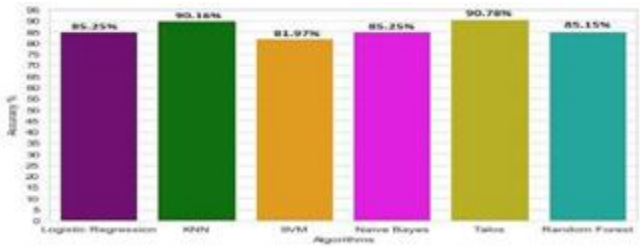
In this paper we applied some classification algorithms (like – K-NN, SVM, and Hyper-parameter optimization) on Heart diseases data set and measure the all classification accuracy is available in Table 2.

Table 2 - Algorithms accuracy comparison

S.No.	Classification Algorithms	Accuracy
1.	Logistic Regression	**85.25%**
2.	K-NN	**90.16%**
3.	SVM	**81.97%**
4.	Precision,	**75.31%**
5.	F1-score,	**72.22%**
6.	Recall,	**76.11%**
7.	Naïve Bayes	**85.25%**

8.	Hyper-parameter optimization (Talos)	**90.78 %**
9.	Random forest	**85.15%**

In this paper, we finally found out the best classification algorithms is Hyper-parameter optimization using Talos for Heart diseases dataset.



4.0. Conclusion

A summary of this paper arranged in a logical sequence that generally follows your methodology section. Compare to other algorithms and optimization, it is proved good results for prediction. In this paper, we deploy a deep learning neural networks (DNN) using Talos optimization. Talos optimization is newly optimization techniques in DNN. Talos provide better accuracy (90.76%) to other optimizations. It is applied on the heart disease datasets and find out the good prediction. Using the Talos optimization we create a Keras model and deploy it.

Limitations:

1. Data Availability and Quality: One significant limitation in cardiovascular disease prediction using deep learning neural network models is the availability and quality of data. While there is a vast amount of healthcare data, including electronic health records, medical imaging, and genetic information, obtaining high-quality, well-curated datasets with sufficient sample size can be challenging. Biases and inaccuracies in the data can lead to biased model predictions and reduced generalization capabilities.
2. Interpretability: Deep learning models are often criticized for their lack of interpretability. While these models can achieve high accuracy in prediction tasks, understanding the rationale behind their decisions remains a challenge. In the context of cardiovascular disease prediction, interpretability is crucial for gaining insights into the underlying risk factors and mechanisms contributing to disease onset and progression.
3. Generalization: Deep learning models trained on specific datasets may lack generalization when applied to different populations or healthcare settings. Population-specific variations in demographics, lifestyle factors, genetic predispositions, and healthcare practices can affect the model's performance and reliability across diverse populations.
4. Ethical and Privacy Concerns: The use of sensitive healthcare data raises ethical and privacy concerns regarding patient confidentiality, data security, and informed consent. Ensuring compliance with data protection regulations, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States, while facilitating data sharing and collaboration among researchers, presents a significant challenge.

Areas of Further Research:

1. Transfer Learning and Domain Adaptation: Investigating techniques like transfer learning and domain adaptation can enhance the generalization capabilities of deep learning models for cardiovascular disease prediction. By leveraging knowledge from pre-trained models or adapting models to different target domains, researchers can address issues related to data scarcity and population heterogeneity.
2. Explainable AI (XAI): Developing explainable AI techniques for deep learning models can improve transparency and interpretability, enabling clinicians and healthcare practitioners to trust and validate model predictions. Exploring methods for generating interpretable feature representations and visualizing model decision-making processes can facilitate better understanding and acceptance of AI-driven healthcare applications.
3. Multi-Modal Data Fusion: Integrating diverse sources of healthcare data, including clinical, imaging, genomic, and wearable sensor data, through multi-modal data fusion techniques can enhance the predictive power of deep learning models for cardiovascular disease prediction. By capturing complementary information from different modalities, researchers can uncover complex relationships and biomarkers associated with disease risk and progression.
4. Clinical Validation and Real-World Deployment: Conducting rigorous clinical validation studies and evaluating the real-world performance of deep learning models for cardiovascular disease prediction is essential for their clinical adoption and deployment. Collaborating with healthcare institutions, clinicians, and regulatory agencies to validate model efficacy, safety, and cost-effectiveness can facilitate the translation of research findings into clinical practice.

In summary, while deep learning neural network models hold promise for cardiovascular disease prediction, addressing limitations related to data availability, interpretability, generalization, and ethical concerns, and exploring avenues for further research, will be critical for realizing their full potential in improving cardiovascular healthcare outcomes.

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