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FORECASTING CARDIOVASCULAR HEALTH USING DEEP LEARNING

[1*]Ganesh Khekare, [2]Akkireddi S V S Rama Prasada Rao, [3]B R Jagadeeshwar Sai, [4]Dileep Kumar Reddy
School of Computer Science and Engineering,
Vellore Institute of Technology, Vellore, India
khekare.123@gmail.com*

Abstract: Heart disease is currently the leading cause of death globally and its prevalence is increasing. Detecting heart disease early is challenging, despite the abundance of data available in clinics and hospitals. However, machine learning has the potential to analyze this data and provide valuable insights, leading to improved decision support systems. Previous research has focused on deep learning techniques, and this study utilizes a Keras-based deep learning model with a thick neural network to accurately diagnose heart problems. The model is evaluated using various combinations of hidden layers and neurons, and the results are measured using sensitivity, specificity, accuracy, and f-measure. The study finds that the proposed deep learning model outperforms individual models and ensemble approaches in terms of accuracy, sensitivity, and specificity across all heart disease datasets that were tested.

***IndexTerms* – Health Insurance, Cardiovascular Disease, Neural Network, Deep Learning, Health Informatics.**

I. INTRODUCTION

Heart disease, also known as circulatory illness, is the leading cause of death worldwide and its prevalence is increasing. Most people are unaware of the symptoms of heart disease, such as chest discomfort, sweating, and fatigue, until they have a heart attack. Doctors use physical examinations, medical histories, and tests like chest X-rays to diagnose heart disease, but sometimes the symptoms don't align with the objective findings. Medical professionals believe that many heart attack and stroke victims are not considered "at risk" and one-third of patients are misdiagnosed. Early detection is challenging because symptoms like tiredness and chest discomfort can also be signs of other conditions. As a result, detecting heart disorders is becoming more challenging for doctors, as many individuals only exhibit symptoms during a sudden heart attack.

1.1 OBJECTIVE

The main objective is to develop a deep learning model that can accurately detect heart issues by using four different sets of heart disease data. Multiple-layer deep neural networks are utilized to achieve precise results in the analysis. Data estimation techniques are employed to enhance the accuracy of the model. Two studies demonstrate the effectiveness of the model, one using individual classifiers and the other using group classifiers.

1.2 PROBLEM STATEMENT

Heart disease is currently the leading cause of death globally and is on the rise. Detecting heart disease early is crucial to preventing heart events. Despite the abundance of information on heart disease in medical settings, there is a lack of smart analysis to uncover hidden patterns. Machine learning techniques offer a solution to converting medical data into valuable insights.

1.3 SOFTWARE REQUIREMENTS

Software requirements list the computer resources and system requirements needed for a program to run well. These needs are seldom supplied with program downloads. Install these individually before loading the program.

- Software: Anaconda
- Primary Language: Python
- Frontend Framework: Flask
- Back-end Framework: Jupyter Notebook

- Database: Sqlite3
- Front-End Technologies: HTML, CSS, JavaScript and Bootstrap4

1.4 HARDWARE REQUIREMENTS

Every OS and software needs hardware or computer tools. Hardware requirements lists frequently include a hardware compatibility list (HCL). In particular, operating systems. Hardware included in an HCL has been tested with a certain operating system or software. The following are hardware requirements.

- Operating System: Windows Only
- Processor: i5 and above
- Ram: 8 GB and above
- Hard Disk: 25 GB in local drive

II. LITERATURE SURVEY

3.1 On deep neural networks for detecting heart disease:

Heart disease kills most people, and specialists believe half of all heart attacks and strokes occur in non-at-risk adults. Thus, improving heart disease diagnosis immediately is crucial. We investigate how data analysis, particularly deep neural networks (DNNs), may detect cardiac disease in clinical data. Building, testing, and improving DNN systems with additional layers for heart disease diagnosis is our core focus. This investigation revealed that HEARO-5, a five-layer DNN architecture, made the most accurate predictions. HEARO-5 manages missing data and outliers naturally via regularization optimization. We test and enhance designs and evaluate classes using k-way cross-validation and Matthews' correlation coefficient (MCC). The public Cleveland medical data is used in the research. Our modifications are open source to make health DNN research simpler to access and perform. The HEARO-5 design outperforms the previous research with 99% accuracy and 0.98 MCC.

3.2 Analytical study of heart disease diagnosis using classification techniques:

Heart disease is a major concern worldwide, and it causes more deaths than the initial heart attack itself. Complications can arise in individuals with heart attacks, breast cancer, lung cancer, or heart issues. It is important to have a precise method for determining the prevalence of heart disease in various cases. This research examined nine different algorithms for detecting heart disease, including decision trees, basic Bayesian neural networks, and SVM.ANN, CNN. The recommendation was to use Apriori with SVM for detecting cardiac disease. The study used medical profiles, such as age, gender, blood pressure, chest pain type, and fasting blood sugar, to predict the risk of heart disease. Medical professionals are interested in identifying and treating heart issues, and the research found that classification-based strategies are more accurate and effective.

3.3 Comparative analysis of data mining techniques to predict heart disease for diabetic patients:

The healthcare industry faces challenges in detecting illnesses, but data mining can help providers analyze patient data effectively. This study compares three data mining methods (Naïve Bayes, Support Vector Machine, and Decision Tree) to determine the best approach for predicting heart disease in diabetic patients.

3.4 Comparative analysis of machine learning algorithms for heart disease prediction:

Recently, heart disorders have become a leading cause of mortality worldwide. All across the globe, developed, poor, and emerging nations are facing this terrifying issue. Lifestyle, diet, and work culture changes are the main causes. Early detection and ongoing monitoring of cardiovascular disorders may reduce patient numbers and mortality. However, there are few medical facilities and qualified physicians, making it difficult to monitor and advise patients. Technology must improve patient monitoring and treatment. Circulatory disease prediction models may be created using medical treatment data and patient monitoring. Early detection of cardiovascular disorders may help high-risk individuals adopt lifestyle adjustments to minimize their risk. This might advance medicine greatly. This research examines common machine learning heart disease prediction approaches using medical data and prior occurrences. We compare approaches and discuss them. This paper examines five main approaches to predicting heart attack risk. KNN, Decision Tree, Gaussian Naive Bayes, Logistic Regression, and Random Forest are employed. The paper also discusses prediction model methodologies' merits and downsides.

3.5 A knowledge-based clinical decision support system utilizing an intelligent ensemble voting scheme for improved cardiovascular disease prediction:

Medical data is abundant and valuable in healthcare. A CDSS helps clinicians make safer judgments for patients. Heart disease is a leading long-term ailment. Many researchers have utilized data mining to predict cardiac disease. The proposed structure improves cardiac disease prediction. This research recommends a group voting mechanism to forecast heart disease. The UCI library included four typical heart disease datasets for testing and studies. Comparing the proposed ensemble's performance with individual classifiers and five ensemble systems with varying parameters. To demonstrate the ensemble scheme's efficacy. Averaging 83% accuracy, the proposed ensemble strategy outperforms competing ensemble systems and individual classifiers.

III. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM:

They previously developed a heart disease diagnosis system by evaluating machine learning approaches on the public 303-record UCI dataset. Six examples were studied. (1) testing classifiers without feature reduction; (2) using only seven relevant attributes for feature reduction; (3) figuring out accuracies after removing generic features; (4) re-sampling and essential attributes; (5) re-sampling all 14 attributes; and (6) using the Synthetic Minority Over Sampling Technique (SMOTE) in Weka. In another article, they described a heart disease diagnosis approach and its key variables. Many methods are used to discover risk factors, including PSO and K-means grouping. After identifying risk indicators, supervised learning groups the data. Three medical files are tested. 335 cases from the Indira Gandhi Medical College, Cleveland heart disease data, and Indian patient data were used.

3.1.1 Disadvantages of the proposed system

1. Their method can only be used with a single dataset.
2. The current work uses several machine learning methods, such as resampling and feature reduction, but it doesn't improve the selection of features or make more correct estimates.
3. The current work chooses only 7 important traits, which is a very simple way to reduce the number of features. This could cause things to be oversimplified and leave out aspects that might be useful.
4. The current work doesn't talk about ensemble methods, which use more than one model to make more accurate predictions. It's possible that this would make it harder to improve efficiency by combining models.
5. PSO and K-means grouping may give us risk factors, but they might not be as easy to understand or directly linked to medical knowledge as traits found by a deep neural network.

3.2 Proposed System:

We recommend using deep learning to construct a heart disease diagnosis decision support system (DSS). We recommend a Keras-based deep learning model with a dense neural network for heart disease detection. The model is tested using 3–9 dense neural network hidden layers. Every layer contains 100 neurons and Relu activation. Research on heart disease uses several data sets, and single and group models are evaluated on them. Deep neural network performance is measured by sensitivity, precision, accuracy, and f-measure. Layer combinations vary according to characteristic groupings.

3.2.1 Advantages of the proposed system:

1. Our tests used different arrangements of hidden layers, from 3 to 9 layers, with 100 neurons and the Relu activation function in each. This extra depth and complexity might help pull out features better and make more accurate predictions.
2. It looks like our work uses a more advanced and flexible neural network model that isn't just based on feature reduction.
3. The best thing about using CNN on picture data is that it instantly finds the most important parts.
4. Our thick neural network might make it easier to see which features are most important.

3.3 REQUIREMENTS

3.3.1 FUNCTIONAL REQUIREMENTS

functional requirements refer to the specific capabilities and behaviors that the system must exhibit to fulfill its intended purpose effectively. These requirements outline the functionalities that the machine learning model or system must have to meet its user's or stakeholders' needs. Here are the functional requirements of the project.

- Data Collection
- Feature selection
- Data augmentation
- Training model
- Outcome

3.3.2 NON-FUNCTIONAL REQUIREMENTS

The quality of a software system is described by NON-FUNCTIONAL REQUIREMENT (NFR). They rate the software system on how responsive it is, how easy it is to use, how secure it is, how portable it is, and other non-functional standards that are important to the system's success. "How fast does the website load?" is an example of a nonfunctional condition. If the non-functional requirements don't meet standards, the tools might not meet user wants.

- Usability requirement
- Serviceability requirement
- Manageability requirement

- Recoverability requirement
- Security requirement
- Data Integrity requirement
- Capacity requirement
- Availability requirement
- Scalability requirement
- Interoperability requirement
- Reliability requirement
- Maintainability requirement
- Regulatory requirement
- Environmental requirement

IV. DESIGN APPROACH AND DETAILS

4.1 SYSTEM ARCHITECTURE

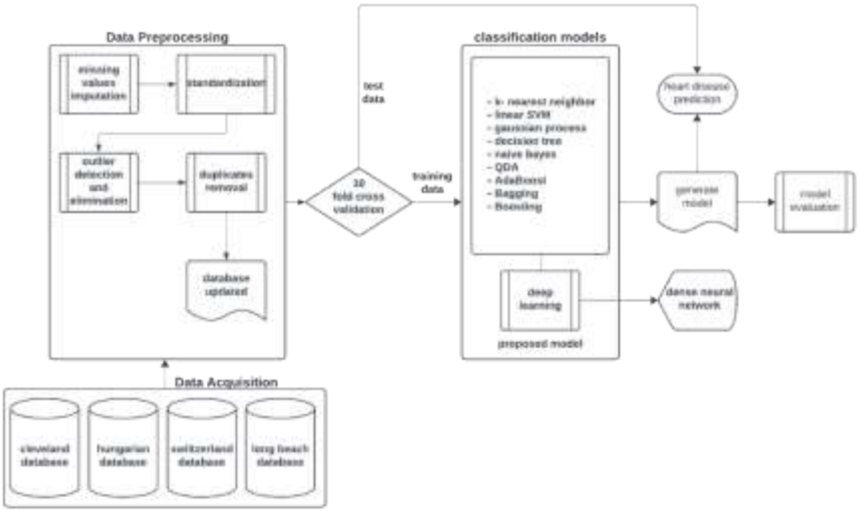


Figure 1. System Architecture

- Data preprocessing: Here all the missing value imputation is done, and the data is standardized. Outlier and duplicate values are detected and eliminated. The database is updated and ready for training and testing.

- The database undergoes 10-fold cross validation and the divided into train and test data.

- The training data is passed and classified through various ML algorithms and DNN with varying layers (3-9 layers).

- The generated model is tested using test data and result values are observed and recorded.

- The recorded values are analyzed and compared to determine the most accurate method for prediction.

  Figure 1 shows the System Architecture.

4.2 DATA FLOW DIAGRAM

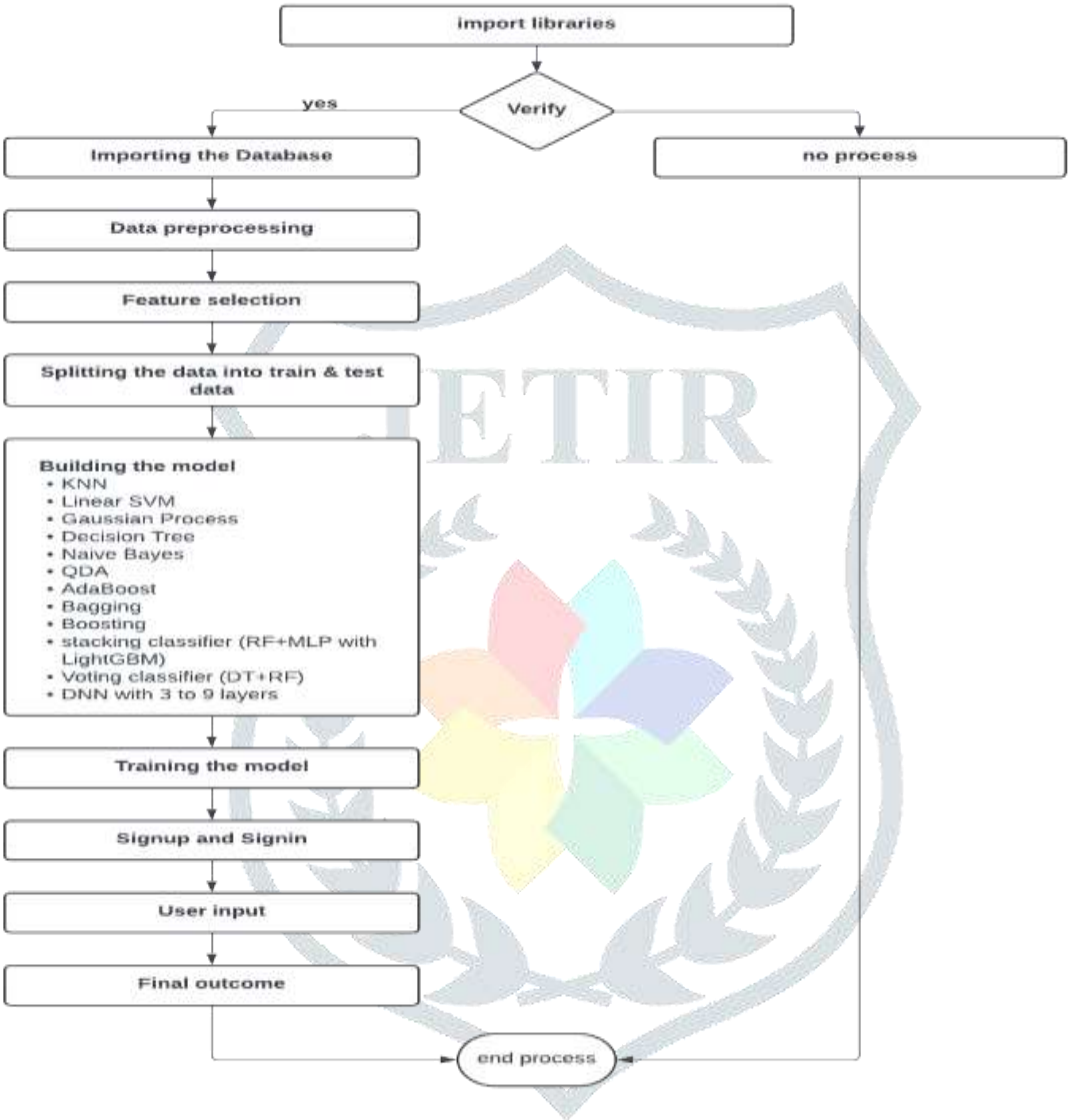


Figure 2. Data Flow Diagram

- All the required libraries are imported.
- The database is imported.
- The data undergoes preprocessing and feature selection.
- The data is split into test and train datasets.
- The training data is sent through different ML algorithms and DNNs with varying layers.
- The model is then integrated with the front end to provide a better user experience.
- The user gives input values, and the model evaluates the values to give accurate results.

Figure 2 shows the data flow diagram.

V. RESULTS AND DISCUSSION

5.1 COMPARATIVE TABLES AND GRAPH

Below are the comparison tables of accuracy, precision, recall, and F1_score of Cleveland, Hungarian, Long Beach-VA, and Switzerland datasets for all the ML algorithms and DL layers (3-9 layers).

Table 1. Performance evaluation- Cleveland- ML

	ml model	accuracy	precision	recall	f1_score
0	KNN	0.600	0.608	0.600	0.593
1	LinearSVC	0.933	0.945	0.933	0.935
2	Gaussian Process	0.533	0.536	0.533	0.525
3	Decision Tree	0.800	0.823	0.800	0.796
4	Naive Bayes	0.867	0.867	0.867	0.867
5	QDA	0.900	0.927	0.900	0.904
6	AdaBoost	0.867	0.871	0.867	0.865
7	Bagging	0.833	0.845	0.833	0.830
8	Boosting	0.833	0.833	0.833	0.832
9	Extension- Stacking Classifier	0.933	0.933	0.933	0.933
10	Extension- Voting Classifier	0.933	0.933	0.933	0.933

Table 2. Performance evaluation- Cleveland- DL

	ML Model	Accuracy		Precision	Recall	F1_score
0	DNN - 3 Layers	0.900		0.900	0.900	0.899
1	DNN - 4 Layers	0.900		0.904	0.900	0.901
2	DNN - 5 Layers	0.867		0.915	0.867	0.875
3	DNN - 6 Layers	0.900		0.904	0.900	0.901
4	DNN - 7 Layers	0.900		0.900	0.900	0.899
5	DNN - 8 Layers	0.367		1.000	0.367	0.537
6	DNN - 9 Layers	0.367		1.000	0.367	0.537

Table 3. Performance evaluation- Hungarian- ML

	ML Model	Accuracy	Precision	Recall	F1_score
0	KNN	0.741	0.783	0.741	0.753
1	Linear SVC	0.704	0.846	0.704	0.745
2	Gaussian Process	0.778	0.778	0.778	0.778
3	Decision Tree	0.778	0.807	0.778	0.774
4	Naive Bayes	0.815	0.814	0.815	0.813
5	QDA	0.815	0.822	0.815	0.817
6	AdaBoost	0.852	0.870	0.852	0.856

7	Bagging	0.778	0.778	0.778	0.778
8	Boosting	0.852	0.858	0.852	0.850
9	Extension- Stacking Classifier	0.778	0.779	0.778	0.775
10	Extension- Voting Classifier	0.778	0.779	0.778	0.775

Table 4. Performance evaluation- Hungarian- DL

	ML Model	Accuracy	Precision	Recall	F1_score
0	DNN - 3 Layers	0.815	0.822	0.815	0.817
1	DNN - 4 Layers	0.778	0.780	0.778	0.775
2	DNN - 5 Layers	0.778	0.778	0.778	0.778
3	DNN - 6 Layers	0.778	0.778	0.778	0.778
4	DNN - 7 Layers	0.593	0.755	0.593	0.603
5	DNN - 8 Layers	0.815	0.814	0.815	0.813
6	DNN - 9 Layers	0.370	1.000	0.370	0.541

Table 5. Performance evaluation- long-beach-VA ML

	ML Model	Accuracy	Precision	Recall	F1_score
0	KNN	0.692	0.938	0.692	0.764
1	Linear SVC	0.615	1.000	0.615	0.762
2	Gaussian Process	0.615	0.771	0.615	0.667
3	Decision Tree	0.615	0.642	0.615	0.625
4	Naive Bayes	0.615	0.771	0.615	0.667
5	QDA	0.615	1.000	0.615	0.762
6	AdaBoost	0.692	0.765	0.692	0.714
7	Bagging	0.538	0.808	0.538	0.646
8	Boosting	0.692	0.765	0.692	0.714
9	Extension- Stacking Classifier	0.792	0.854	0.792	0.816
10	Extension- Voting Classifier	0.792	0.854	0.792	0.816

Table 6. Performance evaluation- long-beach-VA – DL

	ML Model	Accuracy	Precision	Recall	F1_score
0	DNN - 3 Layers	0.769	0.908	0.769	0.800
1	DNN - 4 Layers	0.769	0.908	0.769	0.800
2	DNN - 5 Layers	0.615	1.000	0.615	0.762
3	DNN - 6 Layers	0.615	1.000	0.615	0.762

4	DNN - 7 Layers	0.615	1.000	0.615	0.762
5	DNN - 8 Layers	0.615	1.000	0.615	0.762
6	DNN - 9 Layers	0.615	1.000	0.615	0.762

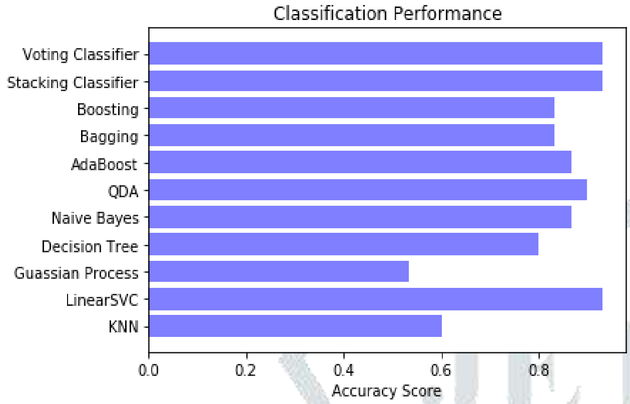
Table 7. Performance evaluation- Switzerland- ML

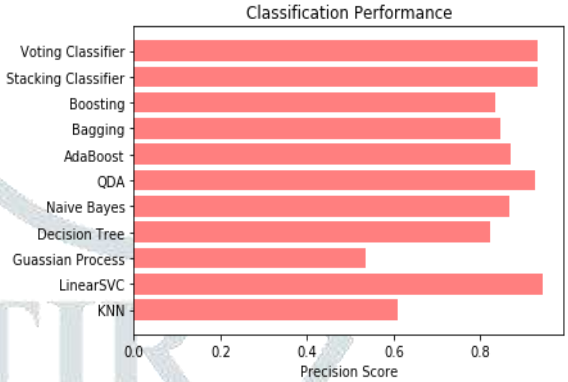
	ML Model	Accuracy	Precision	Recall	F1_score
0	KNN	0.909	1.000	0.909	0.952
1	Linear SVC	0.818	0.818	0.818	0.818
2	Gaussian Process	0.909	1.000	0.909	0.952
3	Decision Tree	0.727	0.655	0.727	0.689
4	Naive Bayes	0.455	0.782	0.455	0.367
5	QDA	0.909	1.000	0.909	0.952
6	AdaBoost	0.818	0.818	0.818	0.818
7	Bagging	0.636	0.509	0.636	0.566
8	Boosting	0.818	0.818	0.818	0.818
9	Stacking Classifier	0.876	0.884	0.876	0.880
10	Voting Classifier	0.876	0.884	0.876	0.880

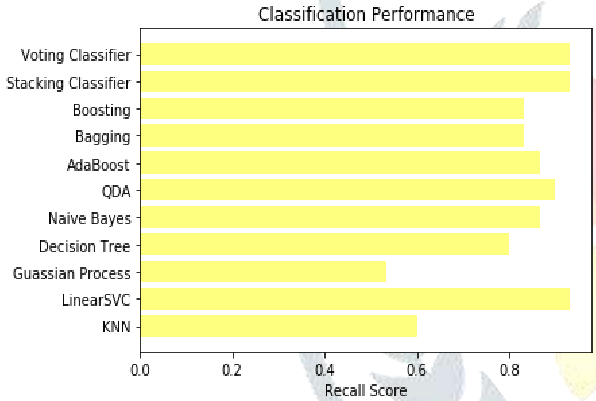
Table 8. Performance evaluation- Switzerland – DL

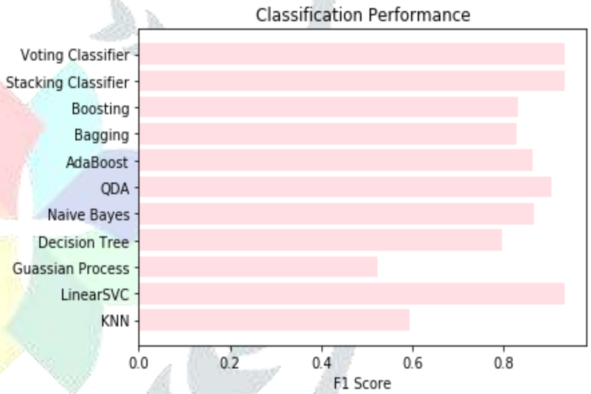
	ML Model	Accuracy	Precision	Recall	F1_score
0	DNN - 3 Layers	0.909	1.0	0.909	0.952
1	DNN - 4 Layers	0.909	1.0	0.909	0.952
2	DNN - 5 Layers	0.909	1.0	0.909	0.952
3	DNN - 6 Layers	0.909	1.0	0.909	0.952
4	DNN - 7 Layers	0.909	1.0	0.909	0.952
5	DNN - 8 Layers	0.909	1.0	0.909	0.952
6	DNN - 9 Layers	0.909	1.0	0.909	0.952

Here are the comparison graphs of accuracy, precision, recall and F1_scores related to Cleveland dataset for all ML algorithms.









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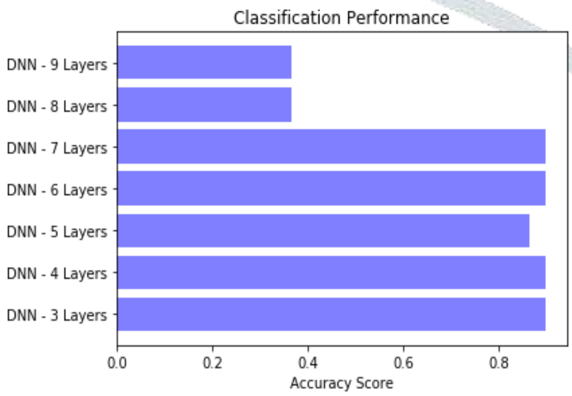

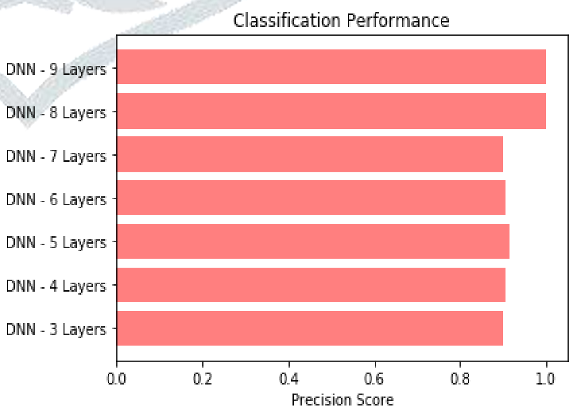

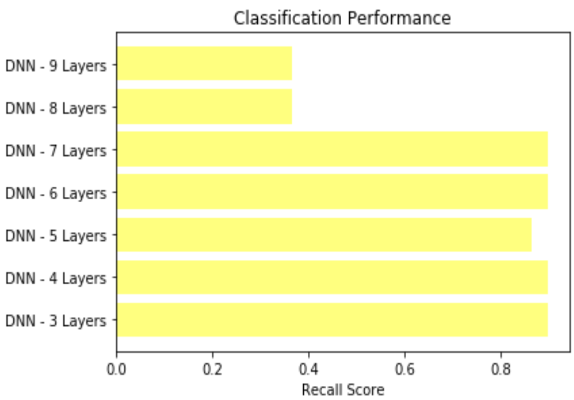

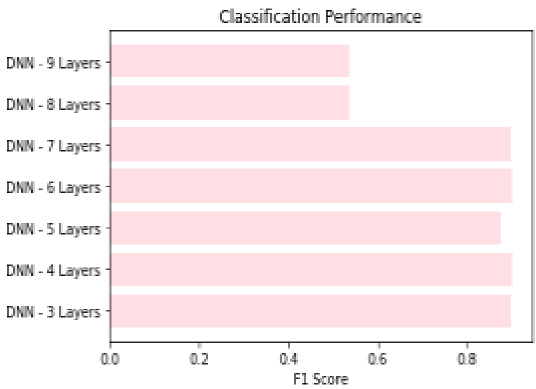

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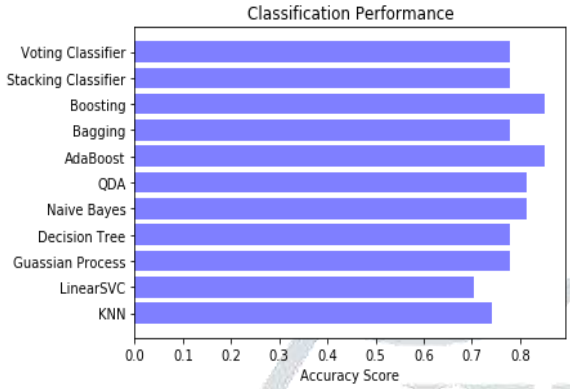

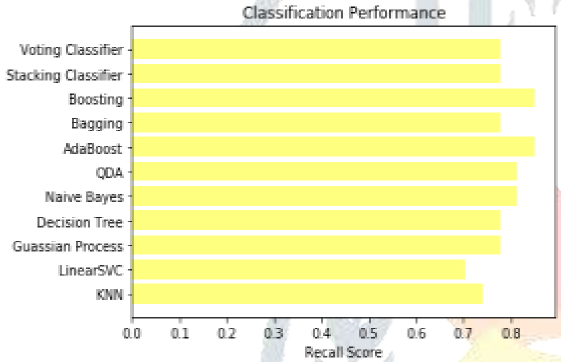

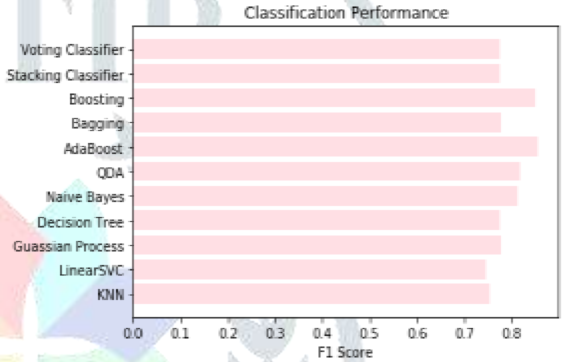

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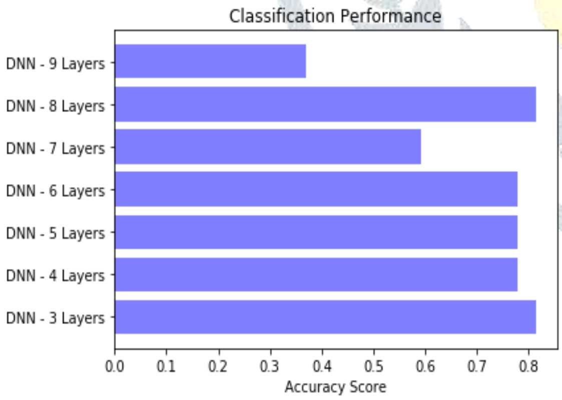

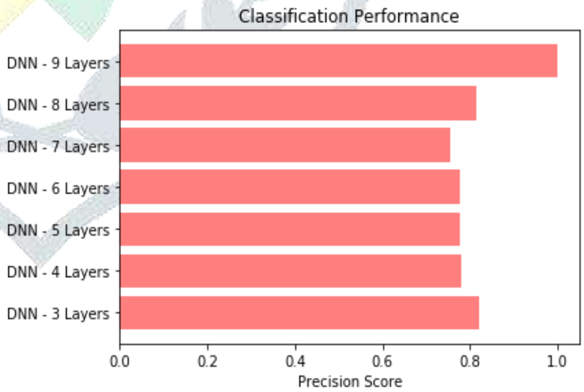

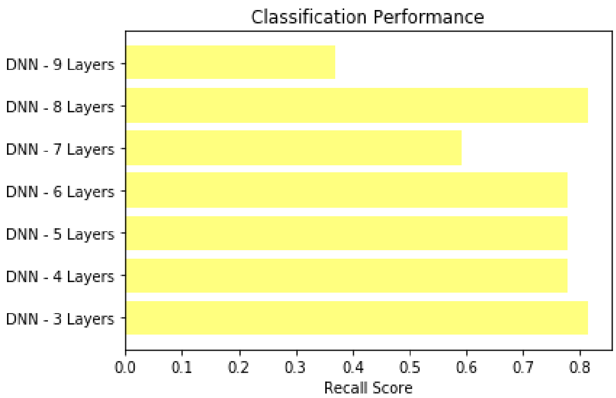

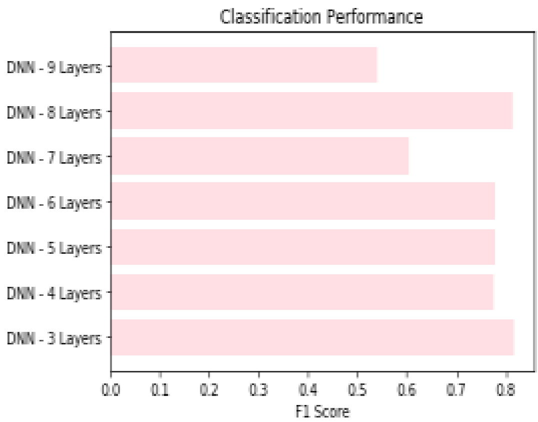

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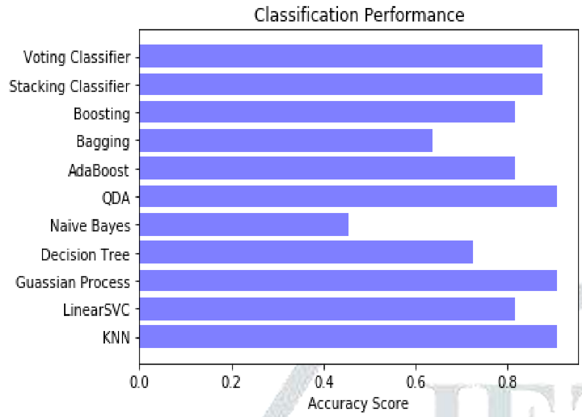

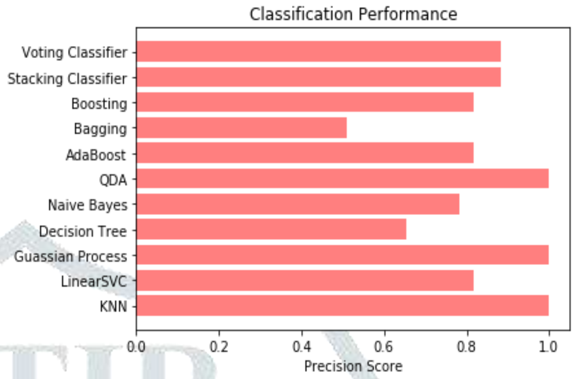

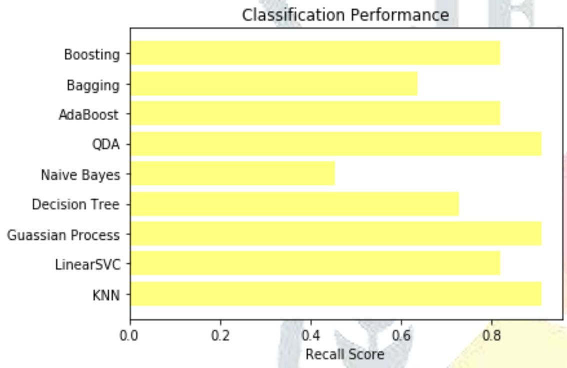

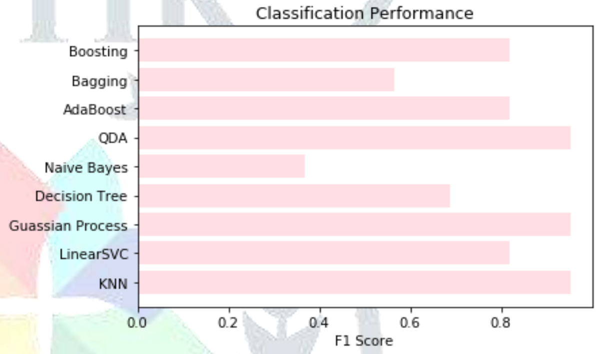

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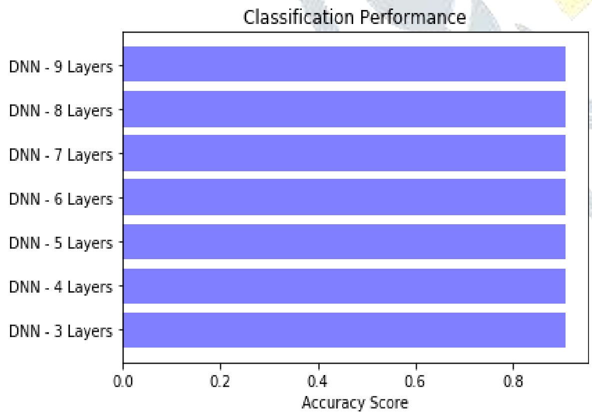

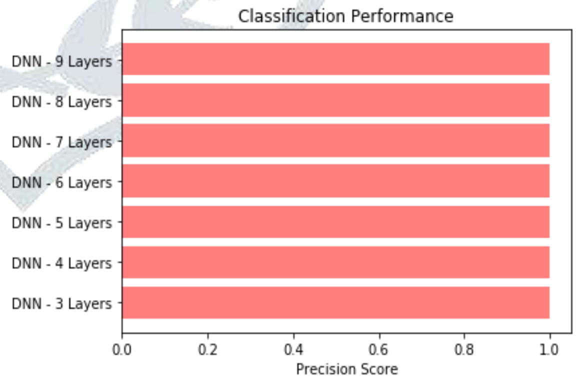

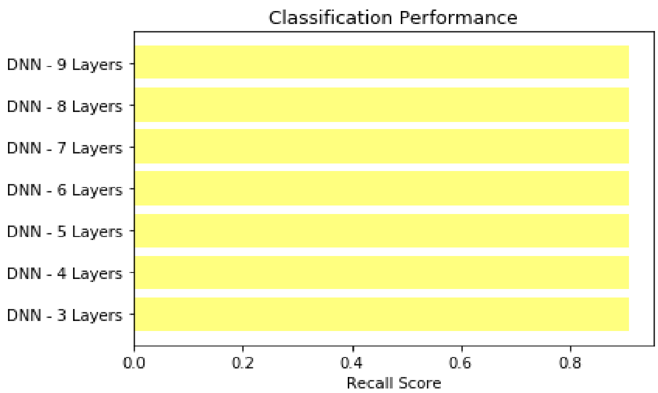

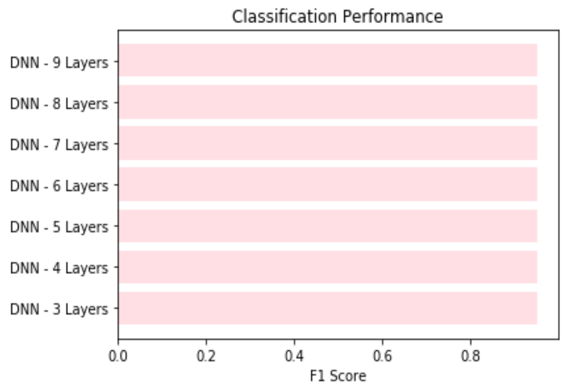

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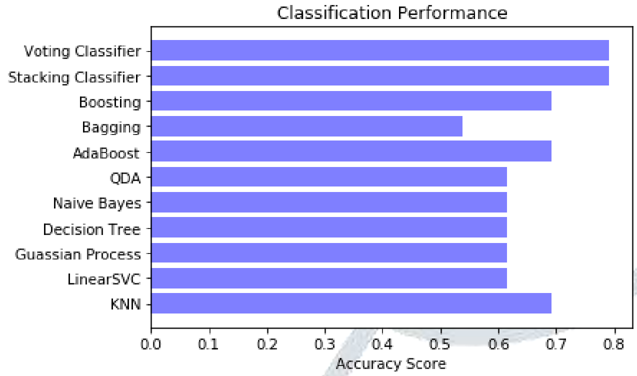
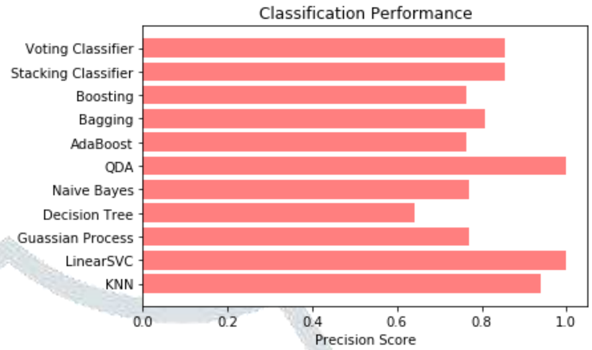
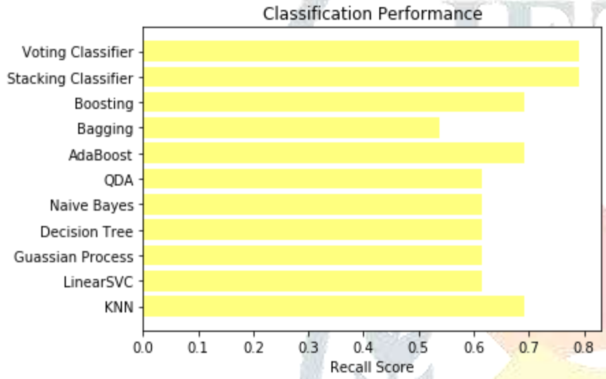
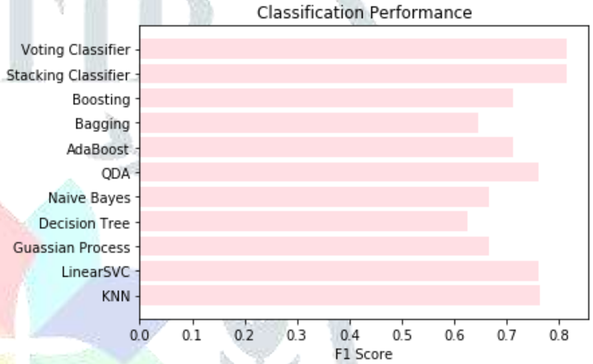
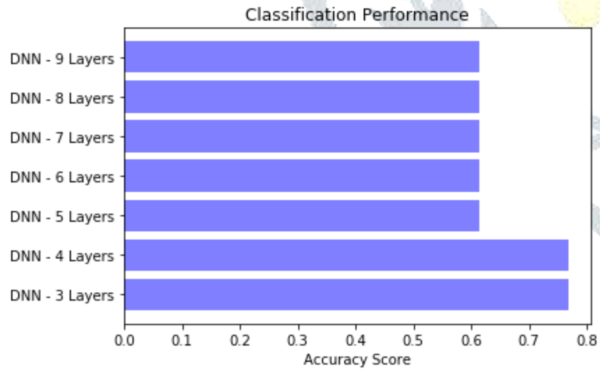


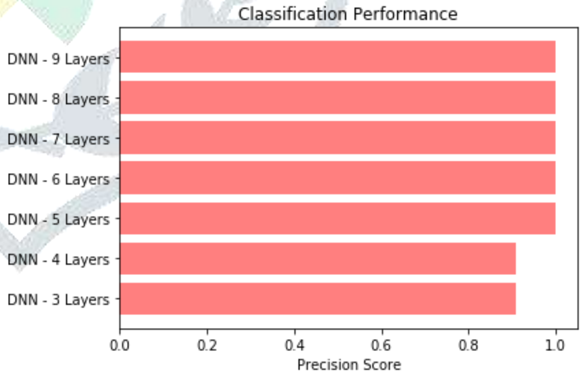


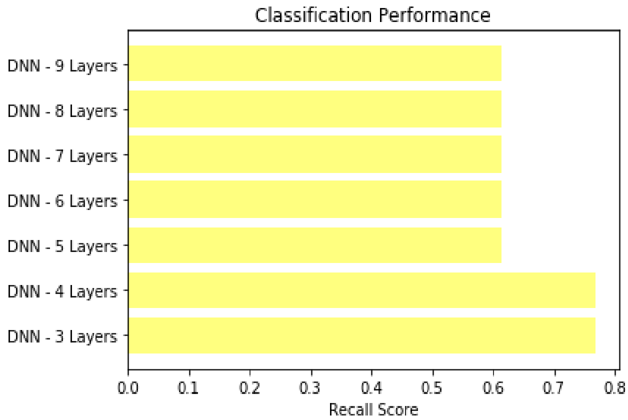


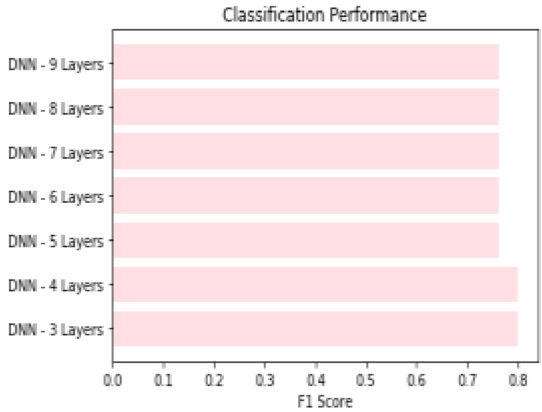


Here are the comparison graphs of accuracy, precision, recall and F1_scores related to long beach-VA dataset for all DL algorithms.









VI. Conclusion And Future Scope

Deep learning has been shown to be a good and accurate way to diagnose and predict heart problems. In terms of accuracy, sensitivity, and precision, the suggested model did much better than other methods. In the future, we want to improve this method by adding picture data from people who have heart problems. These pictures will be made through tests in the lab and medical imaging processes. Convolutional Neural Network (CNN) will also be used on this video data to help make correct diagnoses of heart illnesses. One remarkable thing about using CNN on the picture data that was given is that it automatically finds important traits. The model will also be judged by other performance measures, such as the uncertainty matrix, the PR curve, and the ROC curve. Another thing that might make CNN algorithms better at predicting heart disease is using both organized and random data with the CNN model.

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