Application of machine learning techniques to predict the probability of various chronic diseases.

Abstract: This research study focuses on contributing to the healthcare industry through the proposal of an e-diagnosis or prediction system which functions through the implementation of machine learning models. This study focuses on the analysis of chronic diseases using machine learning techniques such as , utilising datasets provided online, that is, from Mendeley Data and Kaggle. Datasets related to Diabetes and Heart failure are employed to build reliable prediction models. The system aims to process the datasets and develop predictions after splitting the data to train and test the preprocessed datasets. The predictive models encompass in specific, Diabetes and Cardiovascular disease(resulting in Heart failure), on which following techniques are employed; logistic regression, random forest, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), naive bayes (Bernouilli) and Neural Network. The performance of each model in terms of its accuracy, precision, F1 score, etc. have been assessed in order to evaluate their overall efficiency in dealing with the pre-processed datasets and to further enhance the models applied.

Keywords: e-diagnosis, diabetes, cardiovascular, random forest, SVM, KNN, naive bayes, neural network

1.INTRODUCTION

All over the world, chronic diseases are a critical issue in the healthcare domain. According to the medical statement, due to chronic diseases, the death rate of humans increased up to 67% in the past few years. The treatments given for this disease consume over 70% of the patient's income. Hence, it is highly essential to minimise the patient's risk factor that leads to death. This can be done in different ways but the focus in this study is to use machine learning models to identify patterns among patients and their medical results using supervised learning, that is, by training the model using datasets with the outcome mentioned as well. Such models could allow the early detection of chronic diseases such as diabetes and heart related issues, which is our primary focus in this research project.

The advancement in medical research makes health-related data collection easier The healthcare data includes the demographics and medical analysis reports. This platform combines machine learning methods to explore the commonly used computing methods in cardiology and diabetes, such as logistic regression, random forests, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naive Bayes (Bernoulli), AdaBoost and Neural networks. By comparing the accuracy of seven algorithms for predicting chronic diseases, we aim to improve the accuracy of chronic disease prediction, in particular diabetes and cardiac issues by providing the best medical product and service in terms of early diagnosis of such medical issues.

2.MACHINE LEARNING

Endowing machines with the ability to learn like humans is akin to a dream, as machines lack inherent intelligence. The disparity between human and machine capabilities lies in intelligence, where humans can learn from past experiences, a capacity absent in machines that must be programmed with specific instructions. Presently, machine learning enables computers to learn from experiences, a departure from traditional computational algorithms that relied on hard-coded instructions explicitly provided for problem-solving. Thus, this study aims to make use of machine learning to accurately make predictions for early diagnosis of diabetes and heart failure.

Machine Learning applications in healthcare:

Machine learning (ML) has played a pivotal role in revolutionising healthcare, streamlining intricate tasks and enhancing overall efficiency. These technologies not only reduce costs but also expedite drug discovery and enhance therapeutic outcomes, garnering significant attention and investment from healthcare stakeholders while also presenting unprecedented opportunities in the healthcare industry

ML applications in healthcare can be prove to be extremely beneficial to the area of concern, this can be categorised into three main groups:

1. Improving Available Medical Structures**:**

These applications enhance the performance of existing medical structures. ML-based technologies define specific rule-based tasks, such as classifying digital medical images, improving the accuracy of traditional image processing techniques. For instance, Aindra, a medical company utilizing artificial intelligence and ML, employs a platform for the accurate and swift diagnosis of cancers through medical image classification.

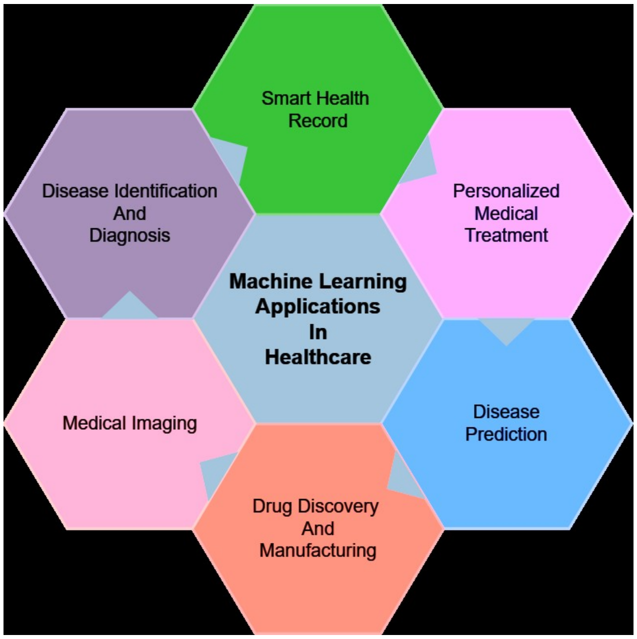
2. Upgrading Medical Structures:

This category focuses on providing medical structures with new capabilities, moving towards personalization. Precision medicine is a notable ML application, tailoring medical treatment to an individual's specific characteristics, such as genetic makeup. Companies like iCarbonx leverage large datasets, biotechnology, and artificial intelligence to advance personalised healthcare services.

3. Independent Medical Structures:

This emerging category involves creating ML-based models capable of independent action based on predefined goals. An intriguing prospect in healthcare is the development of hospitals without physicians, where robots autonomously handle healthcare processes from diagnosis to surgery. While this technology is currently in use for surgeries in some developed countries, it is evolving and undergoing rigorous testing to meet various standards. The Mayo Clinic, for example, is progressing towards a doctor-less hospital, utilising robotic assistance to enhance surgical procedures. Though this technology has imperfections, ongoing advancements indicate its promising future in reshaping healthcare processes.

Figure 1: Machine learning applications in healthcare


Smart Health Record
Disease Identification And Diagnosis
Personalized Medical Treatment
Machine Learning Applications In Healthcare
Medical Imaging
Disease Prediction
Drug Discovery And Manufacturing

Framework for Designing a Learning Model in Medicine

This section outlines the different stages involved in crafting a learning model specifically tailored for the healthcare domain. The intent is to provide researchers with insights into the process of designing a learning model in medicine. We encourage researchers to delve further into this domain to gain a comprehensive understanding and knowledge of learning models. Designing a learning model in healthcare entails five essential phases: problem definition, dataset selection, data preprocessing, development of machine learning (ML) models, and evaluation. Figure 3 illustrates these phases. The subsequent sections elaborate on each of these phases in detail.

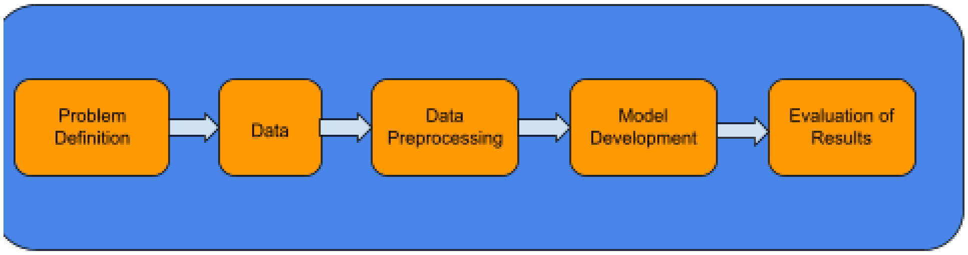


Figure 2: Framework for designing a machine learning model

Literature Review

Victor Chang et al (2022) focused primarily on diabetes for which they made use of the Pima Indian Diabetes Dataset and used techniques such as, PCA, K-means clustering and importance ranking for data pre-processing. Models implemented included Naive Bayes classifier, random forest classifier and J48 decision tree models. In addition to this, feature selection was made use of wherein 3 and 5 factor feature selection was used. They obtained an accuracy of 80-90% using the aforementioned models and techniques.

https://link.springer.com/article/10.1007/s40200-021-00968-z

Ahmad Shaker Abdalrada et al's (2022) study aims to identify people with the co-occurrence of diabetes and cardiovascular diseases. This is a detailed study and analysis which was done using data collected on 200+ variables from more than 2000 patients. Logistic regression and Evimp functions were made use of in multivariate adaptive regression splines models for interpreting the common causes for the co-occurrences of the chronic diseases.

https://link.springer.com/article/10.1186/s12911-019-0918-5

An Dinh et al (2019) make use of different variables and time frames to identify patients with diabetes and cardiovascular diseases. Logistic regression, support vector machines, random forest, and gradient boosting are the models which are made use of in their research study which were then combined to make a weighted ensemble model, which further increased the accuracy of their models. The accuracy came to be around 80% on implementation of the techniques.

https://link.springer.com/article/10.1186/s12902-019-0436-6

Hang Lai et al (2021) made use of 8 features to develop predictive models and used logistic regression along with gradient boosting machine and used adjusted threshold method and class weight method to improve sensitivity. The accuracy of the models came around 70=80% and was compared with machine learning techniques such as decision tree and random forest, to which it performed better than.

Problem definition

According to the National Institute of Health, most people with type 2 diabetes do not have it diagnosed till very late, that is, they are unaware of such asymptomatic (or negligibly symptomatic) problems for up to 4-7 years. In order to tackle the issue, this study focuses on implementation of machine learning models for accurate prediction and diagnosis of underlying diseases. The developed solution would also help in getting early treatment for such non communicable and chronic diseases which would lead to better results in a shorter amount of time.

Dataset and Exploratory Data Analysis

In this research project, the main focus has remained not only on the analysis and development of machine learning models but also on the reliability of the results produced. Being considerate of the diversity and impartial results plays an important role in further enriching Science and our knowledge of it, especially in the healthcare domain. Thus, this research project has covered all the grounds by evaluating two datasets each, for cardiac problems and diabetes, in case of data being collected from a specific group of people sharing similar backgrounds.:

1. Diabetes Dataset - Mendeley Data - (https://data.mendeley.com/datasets/wj9rwkp9c2/1): This dataset is available online via CC by 4.0 This dataset covers data collected from thousand patients making it very usable for this study. This dataset has features in common and different from those covered in the Pima Indian dataset, which would train the model better by covering all grounds of causes of diabetes.
2. Pima Indians Diabetes Dataset - (https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database/code) - Consists of data collected from about 800 patients with 8 features apart from the outcome. Good variance of data and relevant features considered, focusing and pertaining to diabetes.

3. Heart failure dataset (https://www.kaggle.com/datasets/andrewmvd/heart-failure-clinical-data) - Consists of data collected from 300 patients, which is not very large but sufficient for training of data and getting good results. Removal of anomalies and outliers is not encouraged, as the size of the dataset is not big.
4. Heart disease dataset (https://www.kaggle.com/datasets/yasserh/heart-disease-dataset/data) - This dataset too, has data accumulated from 300 patients and all features are relevant to the outcome.

Table 1: Mendeley Data - Data summary

Feature	Description	Data Type	Range
ID	Identification Number of Patient	Numeric	[0,800]
No_Pation	Number of Patient	Numeric	
Gender	Gender (Male/Female)	Characters (M/F)	{M, F}
Age	Age of Patient	Numeric	[20,79]
Urea	Urea levels	Numeric	[0.5,38.9]
Cr	Creatinine ratio	Numeric	[6,800]
HbA1c	Glycated Haemoglobin - Blood glucose level	Numeric	[0.9,16]
Chol	Cholesterol levels	Numeric	[0,10.3]
TG	Triglycerides levels	Numeric	[0.3,13.8]
HDL	High-Density Lipoprotein Cholesterol	Numeric	[0.2,9.9]
LDL	Low-Density Lipoprotein Cholesterol	Numeric	[0.3,9.9]
VLDL	Very Low Density Lipoprotein	Numeric	[0.1,35]

Table 2: Pima Indians Diabetes Dataset - Summary

Feature	Description	Data Type	Range
Pregnancies	No. of Pregnancies	Numeric	[0,17]
Glucose	Glucose levels	Numeric	[0,199]
Blood Pressure	Blood Pressure levels	Numeric	[0,122]
Skin Thickness	Thickness of Skin	Numeric	[0,99]
Insulin	Insulin levels	Numeric	[0,846]
BMI	Body Mass Index	Numeric	[0,67.1]
Diabetes Pedigree Function	Diabetes likelihood	Numeric	[0.078,2.42]
Age	Age of the Patient	Numeric	[21,81]
Outcome	1 - Diabetic 0 - Non Diabetic	Boolean	{1,0}

BMI	Body Mass Index (Weight in Kg/Height in m)	Numeric	[19,47.75]
CLASS	Yes, No or Predicted Diabetes	Characters	{Y,N,P}

Table 3: Heart Failure Dataset - Data summary

Feature	Description	Data Type	Range
age	Age	Numeric	[40, 95]
anaemia	Decrease of red blood cells or haemoglobin	Numeric	{0,1}
creatinine_phosphokinase	Level of the CPK enzyme in the blood (mcg/L)	Numeric	[23,7861]
diabetes	Diabetic or Non Diabetic	Numeric	{0,1}
ejection_fraction	Percentage of blood leaving the heart at each contraction (percentage)	Numeric	[14,80]
high_blood_pressure	High blood pressure - Hypertension	Numeric	{0,1}
platelets	Platelets in blood (kilo platelets/mL)	Numeric	[25100,850000]
serum_creatinine	Level of serum creatinine in the blood (mg/dL)	Numeric	[0.5.9.4]
serum_sodium	Level of serum sodium in the blood (mEq/L)	Numeric	[113,148]
sex	gender	Numeric	{0,1}
smoking	Smokes or not	Numeric	{0,1}
time	Follow-up period (days)	Numeric	[4,285]
DEATH_EVENT	If the patient deceased during the follow-up period	Boolean	{0,1}

Table 4: Heart Disease Dataset - Data summary

Feature	Description	Data Type	Range
age	Age	Numeric	[29,77]
sex	Gender	Boolean	{0,1}
cp	CP levels	Numeric	{0,1,2,3}
trestbps	Resting blood pressure	Numeric	[94,200]
chol	Cholesterol levels	Numeric	[126,564]
fbs	Fasting blood sugar	Boolean	{0,1}
restecg	Patient's Resting ECG Levels	Numeric	{0,1,2}
thalach	Maximum heart rate achieved	Numeric	[71,202]
exang	Patient's Exang Levels	Boolean	{0,1}
oldpeak	Patient's Old Peak History Recorded	Numeric	[0,6.2]
slope	Slope levels	Numeric	{0,1,2}
ca	CA levels	Numeric	{0,1,2,3,4}
thal	Thal levels	Numeric	{0,1,2,3}
target	0 - Healthy 1 - Heart disease patient	Boolean	{0,1}

As may be seen from the data summaries given above, the dataset consisted mostly of numerical values except for a few rows, such as outcome and gender. Working with such inconsistencies in terms of the data type would lead to tedious amounts of work and codes to handle the data. This is why the data was then transformed by converting the binary outcomes, such as M/F or N/Y were made 0s and 1s respectively. The description of the dataset after data transformation has been shown below.

Table 5: Mendeley Data - Data description

	ID	No_Pation	Gender	Age	Urea	Cr	HbA1c	Chol	TG	HDL	LDL	VLDL	BMI	CLASS
count	1688	1688	1688	1688	1688	1688	1688	1688	1688	1688	1688	1688	1688	1688
mean	359.1665	862624.2612559241	0.490521	50.06694	5.03095	66.73934	6.716268	4.597168	2.055219	1.206872	2.628104	1.495438	26.59782	0.5
std	247.8909	7528272	0.500058	9.868652	2.868203	50.39081	2.769452	1.311082	1.347467	0.591841	1.058108	3.005186	5.295642	0.500148
min	1	123	0	20	0.5	6	0.9	0	0.3	0.2	0.3	0.1	19	0
25%	143	34231.75	0	44	3.6	46	4.7	3.8	1.2	0.9	1.8	0.6	22	0
50%	315	34327.5	0	51	4.5	58	5.5	4.4	1.7	1.1	2.5	0.8	24	0.5
75%	600.25	45392	1	56	5.7	73	8.8	5.2	2.4	1.3	3.3	1.2	30	1
max	800	75435657	1	79	38.9	800	16	10.3	13.8	9.9	9.9	35	47.75	1

Table 6: Pima Indians Diabetes Dataset - Data summary

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DPF	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

Table 7: Heart Failure Dataset - Data summary

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	smoking	time	DEATH EVENT
count	299.000000	299.000000	299.000000	299.000800	299.000000	299.000000	299.000000	299.00000	299.000000	299.000000	299.00000	299.000000	299.00000
mean	60.833893	0.431438	581.839465	0.418060	38.083612	0.351171	263358.029264	1.39388	136.625418	0.648829	0.32107	130.260870	0.32107
std	11.894809	0.496107	970.287881	0.494067	11.834841	0.478136	97804.236869	1.03451	4.412477	0.478136	0.46767	77.614208	0.46767
min	40.000000	0.000000	23.000000	0.000000	14.000000	0.000000	25100.000000	0.50000	113.000000	0.000000	0.00000	4.000000	0.00000
25%	51.000000	0.000000	116.500000	0.000000	30.000000	0.000000	212500.000000	0.90000	134.000000	0.000000	0.00000	73.000000	0.00000
50%	60.000000	0.000000	250.000000	0.000000	38.000000	0.000000	262000.000000	1.10000	137.000000	1.000000	0.00000	115.000000	0.00000
75%	70.000000	1.000000	582.000000	1.000000	45.000000	1.000000	303500.000000	1.40000	140.000000	1.000000	1.00000	203.000000	1.00000
max	95.000000	1.000000	7861.000000	1.000000	80.000000	1.000000	850000.000000	9.40000	148.000000	1.000000	1.00000	285.000000	1.00000

Table 8: Heart Disease Dataset - Data summary

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.039604	1.399340	0.729373	2.313531	0.544554
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.161075	0.616226	1.022606	0.612277	0.498835
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000	2.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000	2.000000	1.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000	3.000000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	3.000000	1.000000

It can be said that the diabetes datasets consist of a good variety of data from both the datasets consisting of data collected from almost 2400 patients. Such a large amount of data can aid in evaluating the correct percentage of accuracy of the developed and implemented methods. The cardiac problems' datasets, on the other hand, may not be as large in comparison to diabetes, but do consist of a good amount of data collected from patients of diverse origins.

The datasets also consist of 8-12 relevant features each apart from the outcome which is a good number of factors which should be analysed to aid in prediction of diabetes and cardiovascular diseases.

Data Visualization

In order to get a deeper and better understanding of the datasets and the correlations between various features, heatmaps, bar and dot plots have been used. Such plots of correlations between features and trends in dot plots, for instance, prove very useful in techniques such as feature selection, engineering, etc. The following visualisations were obtained of the datasets and its features:

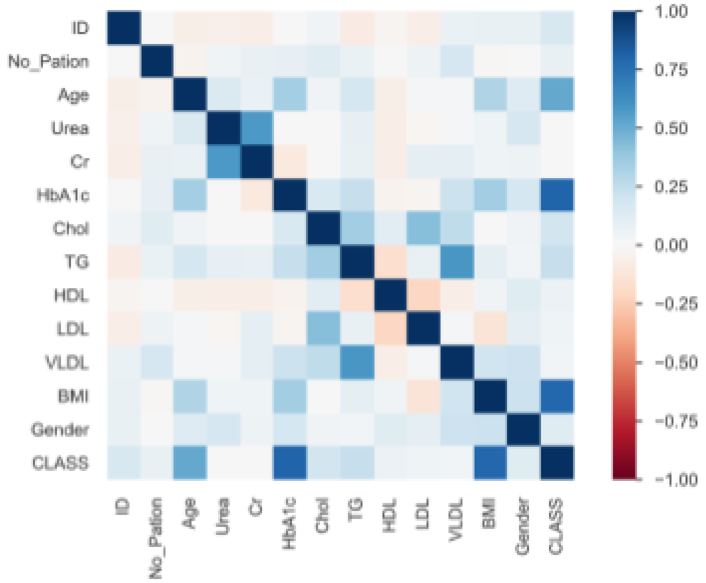


Fig 3: Identifying correlations in Mendeley's Diabetes Dataset

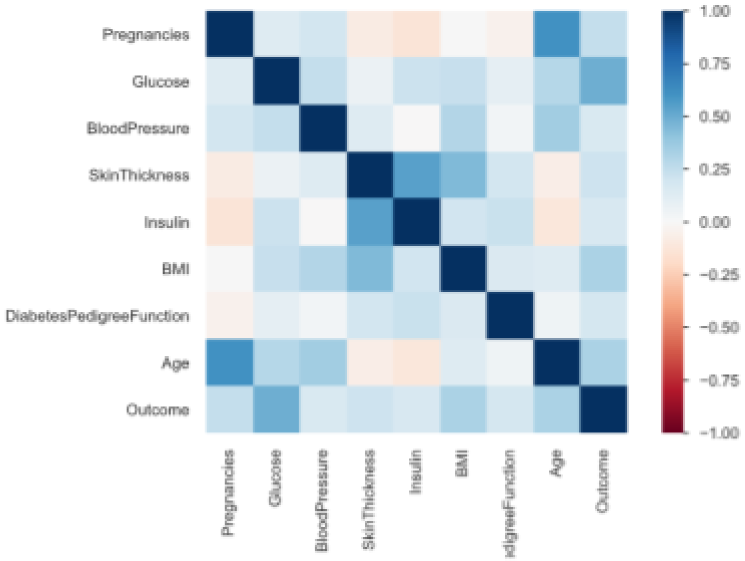


Fig 4: Identifying Correlations in Pima Indians Diabetes Dataset

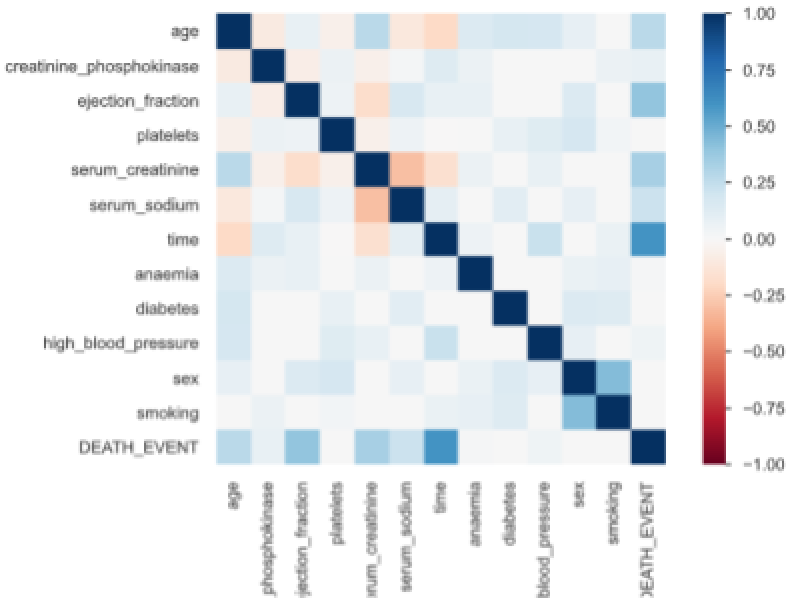


Fig 5: Identifying correlations in the Heart failure dataset

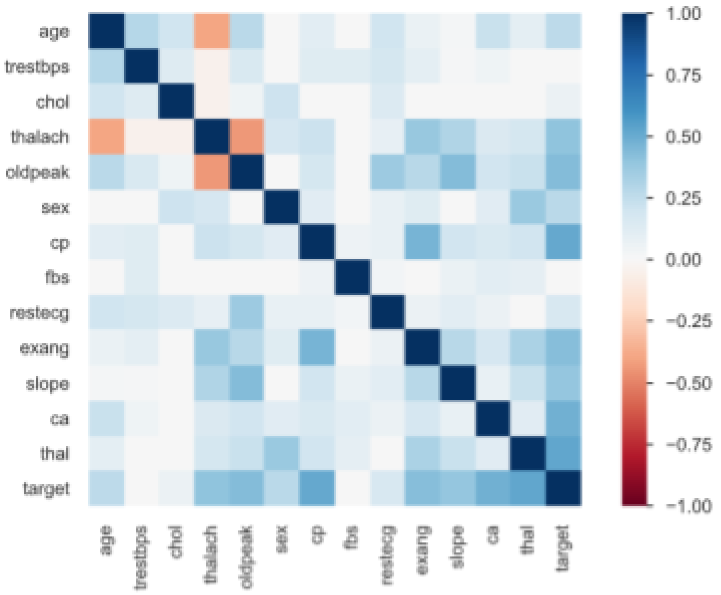


Fig 6: Identifying correlations in the Heart disease dataset

Identifying Correlations:

The datasets were plotted on a heat map to identify correlations among different features and the following was observed:

Age - CLASS	High correlation
Urea - Cr	High correlation
Cr - Urea	High correlation
HbA1c - CLASS	High correlation
TG - VLDL	High correlation
VLDL - TG	High correlation
BMI - CLASS	High correlation
CLASS - Age	High correlation

Similarly, the correlation of the remaining datasets were noted as well.

The datasets were further graphed among different features to display and observe certain trends, such as the given figures obtained from plotting count of diabetic or non diabetic patients against haemoglobin levels as they have a high correlation as can be seen from the figure provided in the previous page. Such graphs are crucial in learning from the dataset in terms of the the range of data available, the extent of credibility and in determining the extent upto which techniques need to be applied to remove anomalies or noise of the data.

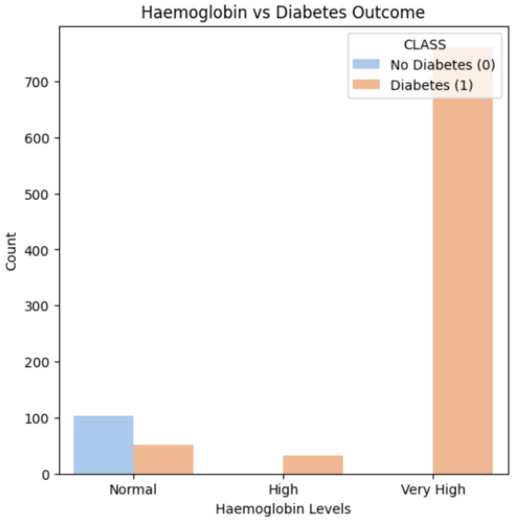


Fig 7: Bar plot of count of diabetic and non diabetic patients

with their haemoglobin values (were highly correlated)

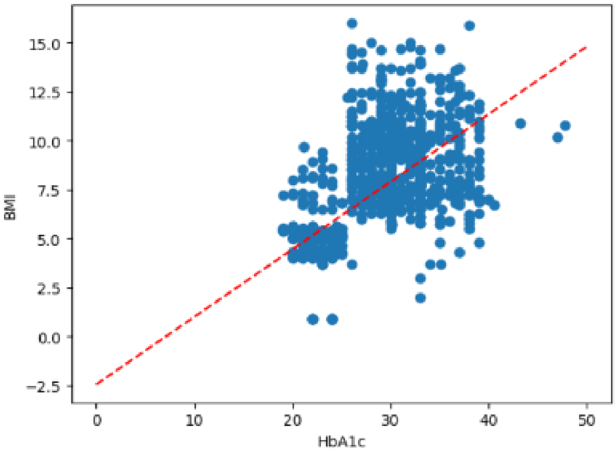


Fig 8: Dot plot of Haemoglobin levels against BMI

Identifying correlations in the Pima Indian Diabetes Dataset

Anomalies remained another concern for which the following box plots were graphed,

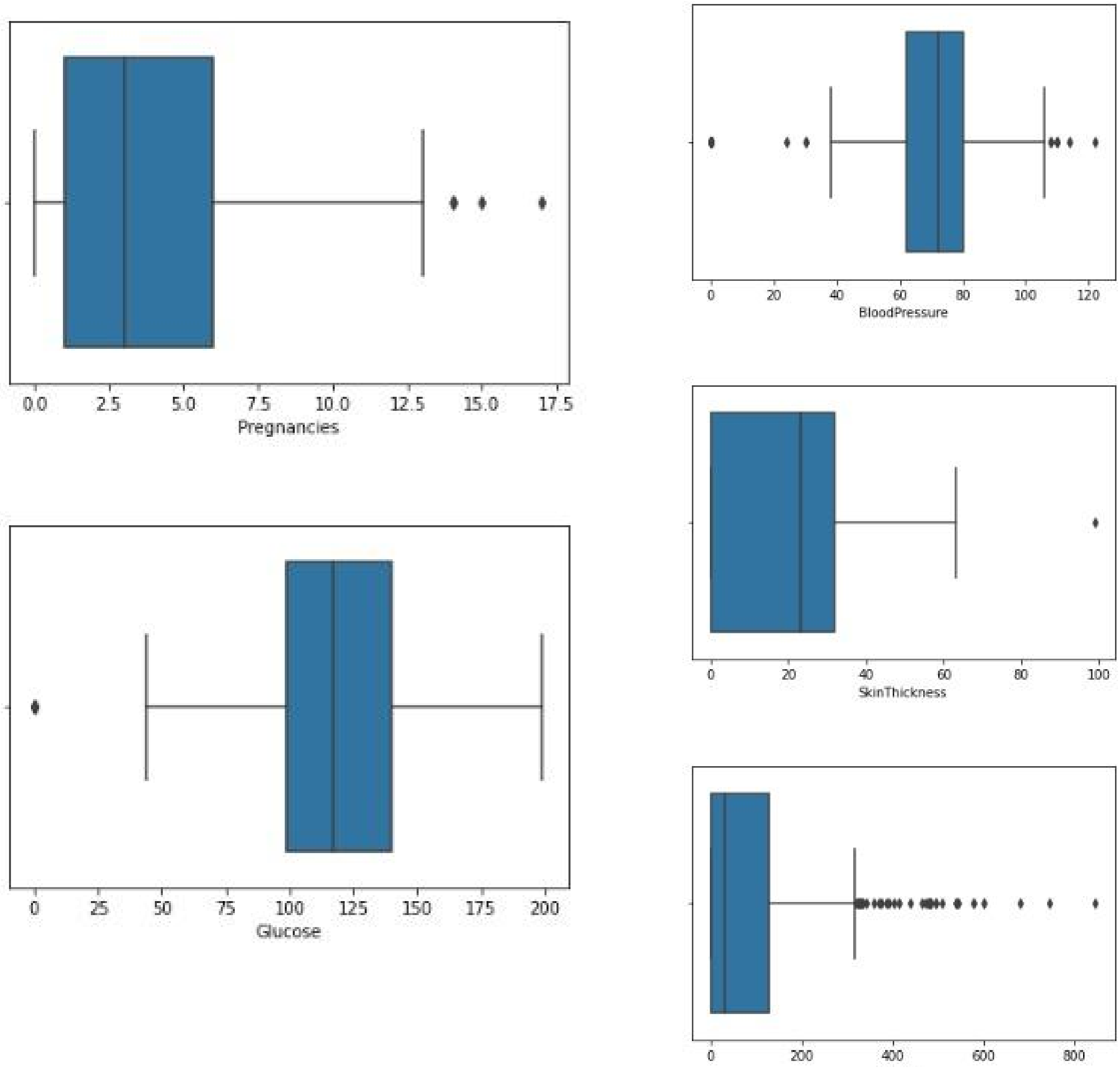


Fig 9: Box plots of features in the Pima Indian Diabetes Dataset

Data Pre-processing

1)Standard Scalar: Firstly, Standard Scaler was used on the dataset, a data preprocessing technique used to standardise the features of a dataset. This approach scales the features so that they have a mean of zero and a standard deviation of one. This is useful when the features of the dataset have different scales. In the Mendeley dataset, the scales had variations in the ranges, which is why the Standardization approach was used as we wanted to bring them to the same scale.

$$z = (x - \mu)/\sigma$$

Where:
z is the standardised value of a data point.
x is the original value of the data point.
μ is the mean (average) of the feature.
σ is the standard deviation of the feature.

2)Principal Component Analysis (PCA): The next pre-processing technique used was Principal Component Analysis (PCA) which is a statistical technique used to reduce the dimensionality of a dataset while retaining most of the original information. This technique is widely used when the dataset is large and has large dimensionality as was in the Mendeley Dataset. It works by identifying a set of orthogonal axes, called principal components, that capture the maximum variance in the data. The principal components are linear combinations of the original variables in the dataset and are ordered in decreasing order of importance.

3)Smoteen/SMOTE: SMOTE - stands for Synthetic Minority Over-sampling Technique, and SMOTEEN (SMOTE-ENN) are two popular techniques used to handle imbalanced datasets in machine learning. Both techniques are oversampling methods that generate synthetic samples of the minority class to balance the class distribution. SMOTE generates synthetic samples by interpolating between existing minority class samples, while SMOTEEN combines SMOTE with ENN (Edited Nearest Neighbors) to remove noisy samples from the majority class.

Selected Models:

1)Logistic Regression: Logistic Regression is a supervised machine learning algorithm that is mainly used for classification tasks where the goal is to predict the probability that an instance belongs to a given class or not. It is a kind of statistical algorithm that analyses the relationship between a set of independent variables and the dependent binary variables. Logistic Regression is a powerful tool for decision-making, for example, email spam or not.

2) Random Forest: A Random Forest is an ensemble learning method for classification, regression, and other tasks that operates by constructing a multitude of decision trees at training time. The output of the random forest is the class selected by most trees.The random forest algorithm is a commonly-used machine learning algorithm that combines the output of multiple decision trees to reach a single result. It handles both classification and regression problems and is known for its ease of use and flexibility.

3)SVM: Support Vector Machine (SVM) is a supervised machine learning algorithm that can be used for classification or regression tasks. The main idea behind SVMs is to find a hyperplane that maximally separates the different classes in the training data. This is done by finding the hyperplane that has the largest margin, which is defined as the distance between the hyperplane and the closest data points from each class. Once the hyperplane is determined, new data can be classified by determining on which side of the hyperplane it falls. SVMs are particularly useful when the data has many features, and/or when there is a clear margin of separation in the data.

4)KNN: K-Nearest Neighbour (KNN) is a non-parametric machine learning algorithm that can be used for both classification and regression tasks. It is based on the principle of similarity, where similar data points are grouped together. The algorithm stores all available cases and classifies new cases based on their similarity to the available cases.The KNN algorithm works by selecting the k nearest neighbours to a given data point and classifying it based on the majority class of these neighbours. The value of k is usually chosen by cross-validation or other methods.

5)Naive Bayes (Bernouilli): Bernoulli Naive Bayes is a variant of the Naive Bayes algorithm that is used for discrete data and works on the Bernoulli distribution. The main feature of Bernoulli Naive Bayes is that it accepts features only as binary values like true or false, yes or no, success or failure, 0 or 1, and so on.The algorithm is based on the principle of conditional probability and assumes that the features are independent of each other. It is commonly used in text classification tasks such as spam filtering, sentiment analysis, and document categorization.

6)AdaBoost - AdaBoost is an ensemble learning technique that boosts the performance of weak learners by sequentially adjusting the sample weights, emphasising misclassified instances, and combining multiple weak classifiers into a strong classifier. It is effective in binary classification problems and applications like face detection and text categorization.

7)Neural Network - A neural network, or artificial neural network (ANN), is a machine learning model inspired by the brain's structure. It consists of interconnected neurons organised into layers with weighted connections and activation functions. Neural networks, especially deep learning models, are widely used for tasks such as image recognition, natural language processing, and reinforcement learning. They are trained to minimise the difference between predictions and actual targets, making them versatile and integral in various fields.

Results of Machine Learning Algorithms

In this research paper, out of the seven models implemented, the models which gave the best results were Logistic regression, Random forest, SVM and Neural Networks. In addition it may be mentioned that for all the models, the same dataset and pre-processing techniques were used as a control environment to compare the results from different models applied.

Table 9: Results obtained from Mendeley's Dataset

Machine Learning Algorithm	Accuracy
Logistic Regression	**1.00**
Random Forest	0.99
SVM	**1.00**
K-Nearest Neighbour	0.99
Naive-Bayes (Bernoulli)	0.89
AdaBoost	0.97
Neural Network	0.98

Table 10: Results obtained from Pima Diabetes Dataset

Machine Learning Algorithm	Accuracy
Logistic Regression	0.84
Random Forest	**0.91**
SVM	0.89
K-Nearest Neighbour	0.85
Naive-Bayes (Bernoulli)	0.73
AdaBoost	0.80
Neural Network	0.90

Table 11: Results obtained from Heart Failure Dataset

Machine Learning Algorithm	Accuracy
Logistic Regression	0.90
Random Forest	0.86
SVM	**0.95**
K-Nearest Neighbour	0.90
Naive-Bayes (Bernoulli)	0.90
AdaBoost	0.90
Neural Network	0.90

Table 12: Results obtained from Heart Disease Dataset

Machine Learning Algorithm	Accuracy
Logistic Regression	0.98
Random Forest	0.93
SVM	0.95
K-Nearest Neighbour	0.98
Naive-Bayes (Bernoulli)	0.95
AdaBoost	0.98
Neural Network	**1.00**

The result will be further tested in terms of precision, recall, f1 Score and AUC:

Accuracy: $(TP + TN)/(TP + TN + FP + FN)$

Precision: $TP/(TP + FP)$

Recall: $TP/(TP + FN)$

F1 Score: $2 * (Precision * Recall)/(Precision + Recall)$

Precision - Precision is a metric in machine learning that measures the accuracy of positive predictions made by a model. It quantifies the proportion of true positive predictions relative to all positive predictions (true positives and false positives). High precision indicates that when the model predicts a positive outcome, it is likely to be correct, making it particularly valuable when minimising false positives is important, such as in medical diagnoses.

Recall - Recall, also known as sensitivity or true positive rate, is a metric that assesses a model's ability to identify all positive instances in the dataset. It measures the proportion of true positives relative to all actual positive instances (true positives and false negatives). High recall suggests that the model is effective at capturing most of the positive cases, making it essential in scenarios where missing positives is costly, such as search and rescue operations.

F1 Score - The F1 Score is a metric that combines precision and recall into a single value. It provides a balanced measure of a model's performance by considering both false positives and false negatives. The F1 Score is the harmonic mean of precision and recall and is useful when you want to strike a balance between precision and recall.

ROC (Receiver Operating Characteristic) - ROC is a graphical representation of a model's performance across different discrimination thresholds. It plots the true positive rate (recall) against the false positive rate as the threshold for classifying positive and negative instances varies. The area under the ROC curve (AUC-ROC) quantifies the overall performance of a model, with higher values indicating better discrimination. ROC curves are often used to evaluate and compare the performance of classification models, especially in scenarios where the trade-off between false positives and false negatives needs to be analyzed.

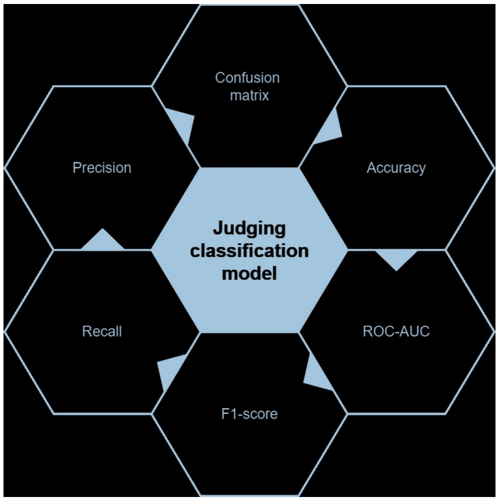


Fig 10: Evaluation models used

Table 13: Mendeley's Diabetes Dataset Model Evaluation:

Model	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F1 Score(%)**	**ROC AUC(%)**
Logistic Regression	100	100	100	100	100
Random Forest	99.09	99.38	98.76	99.07	99.08
SVM	99.70	99.38	100	99.69	99.71
K-Nearest Neighbour	99.09	99.38	98.76	99.07	99.08
Naive Bayes(Bernoulli)	89.12	99.21	78.26	87.50	88.84
AdaBoost	96.98	95.76	98.14	96.93	97.01
Neural Network	98.79	98.16	99.38	98.77	98.81

Table 14: PIMA Indian Diabetes Dataset Model Evaluation:

Model	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F1 Score(%)**	**ROC AUC(%)**
Logistic Regression	83.81	89.83	82.81	86.18	84.09
Random Forest	90.48	89.71	95.31	92.42	89.12
SVM	88.57	88.24	93.75	90.91	87.12
K-Nearest Neighbour	84.76	85.29	90.62	87.88	83.12
Naive Bayes(Bernouilli)	73.33	84.62	68.75	75.86	74.62
AdaBoost	80.00	86.44	79.69	82.93	80.09
Neural Network	89.52	90.77	92.19	91.47	88.78

Table 15: Heart Failure Dataset Model Evaluation:

Model	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)	ROC AUC(%)
Logistic Regression	90.48	84.62	100	91.67	90.00
Random Forest	85.71	78.57	100	88.00	85.00
SVM	95.24	91.67	100	95.65	95.00
K-Nearest Neighbour	90.48	84.62	100	91.67	90.00
Naive Bayes(Bernoulli)	90.48	86.62	100	91.67	90.00
AdaBoost	90.48	86.62	100	91.67	90.00
Neural Network	90.48	86.62	100	91.67	90.00

Table 16: Heart Disease Dataset Model Evaluation:

Model	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)	ROC AUC(%)
Logistic Regression	97.73	100	95.65	97.78	97.83
Random Forest	95.45	100	91.30	95.45	95.65
SVM	95.45	100	91.30	95.45	95.65
K-Nearest Neighbour	97.73	100	95.65	97.78	97.83
Naive Bayes(Bernoulli)	95.45	100	91.30	95.45	95.65
AdaBoost	97.73	100	95.65	97.78	97.83
Neural Network	97.73	100	95.65	97.78	97.83

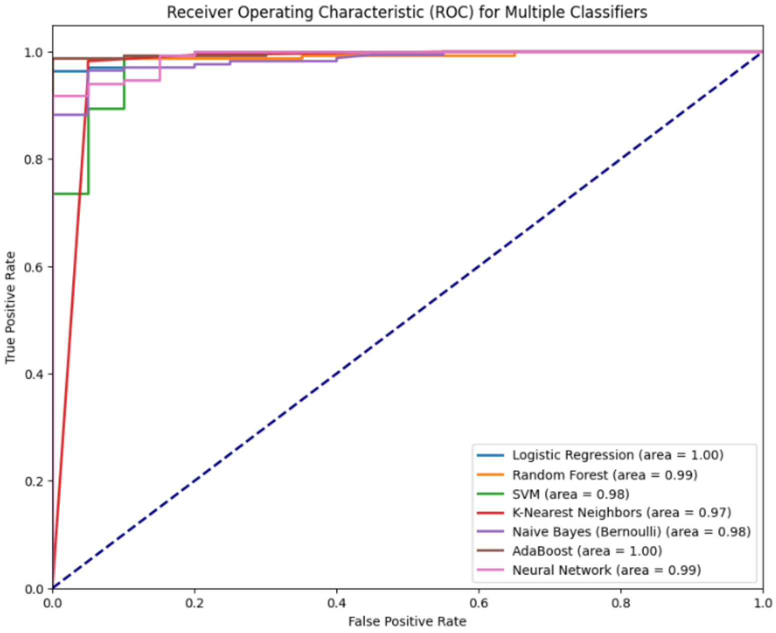


Fig 11: ROC Curve for Mendeley's Diabetes Dataset

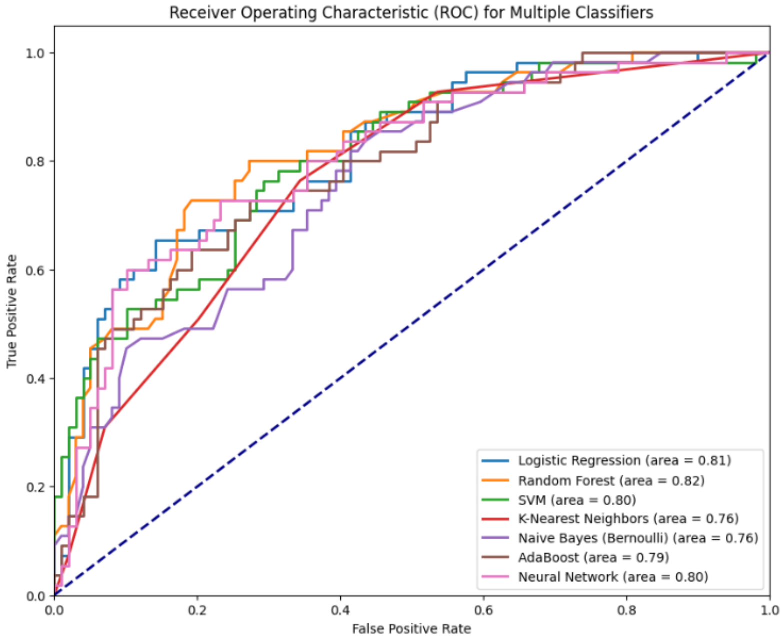


Fig 12: ROC Curve for Pima Indian Diabetes Dataset

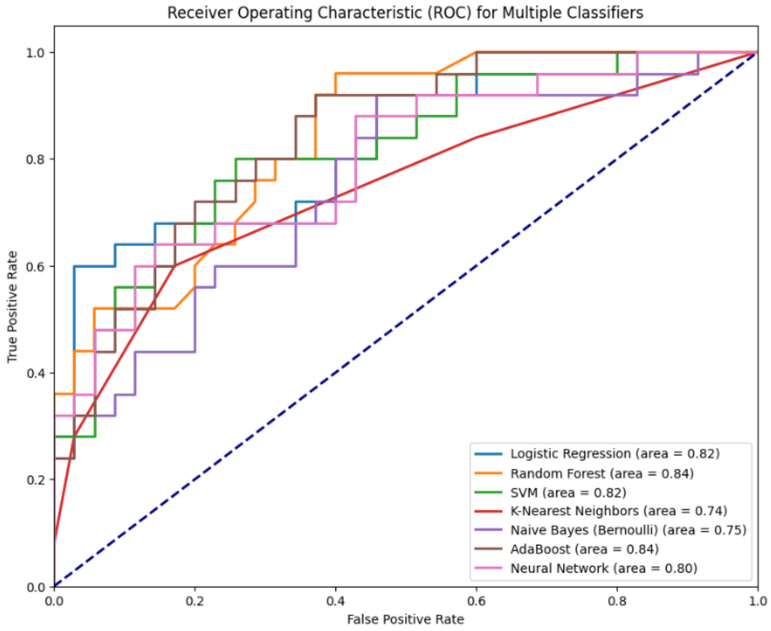


Fig 13: ROC Curve for Heart Failure Dataset

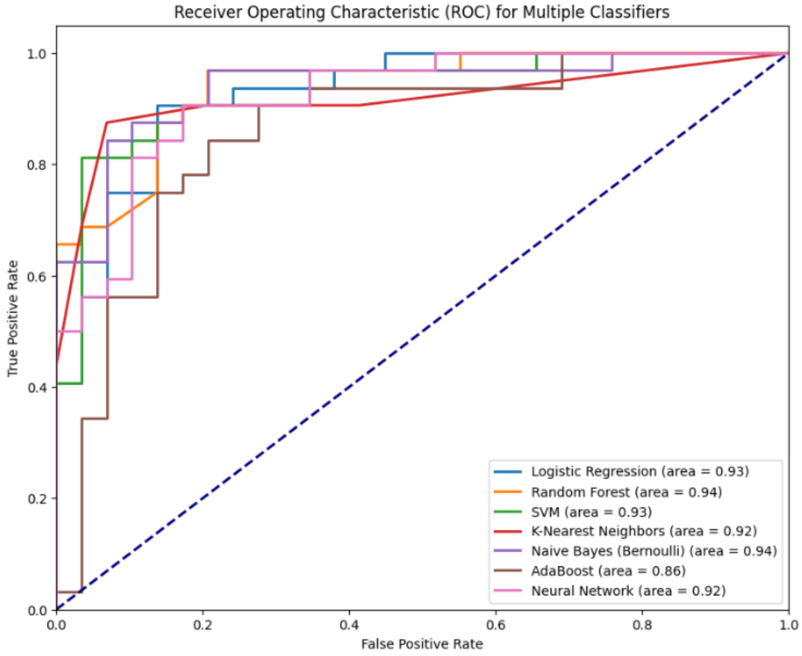


Fig 14: ROC Curve for Heart Disease Dataset

A confusion matrix is a critical tool for evaluating the performance of classification models in machine learning. It presents a structured summary of the model's predictions by distinguishing between true positives (correct positive predictions), true negatives (correct negative predictions), false positives (incorrect positive predictions), and false negatives (incorrect negative predictions). This tabular representation allows for the calculation of essential performance metrics like accuracy, precision, recall, and specificity, helping assess the model's ability to classify data accurately and identify the types of errors it makes in a clear and concise manner.

Table 17: Confusion Matrix Template:

	Actual Positive	Actual Negative
Predicted positive	True positive	False positive
Predicted negative	False negative	True negative

The confusion matrix for each model used for each dataset is shown below:

Fig 15: Mendeley's Diabetes Dataset Confusion Matrices

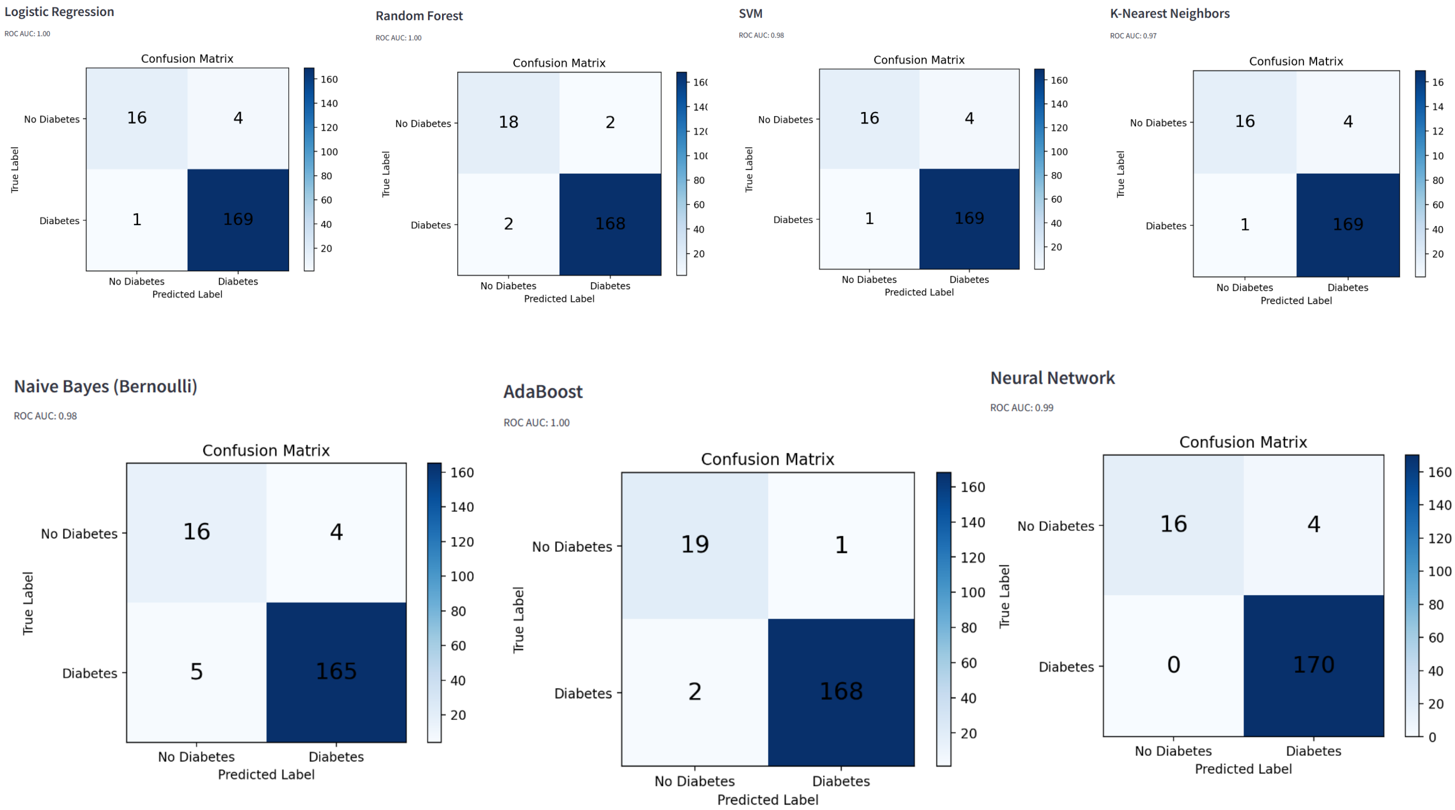


Fig 16: Pima Indians Diabetes Dataset Confusion Matrices

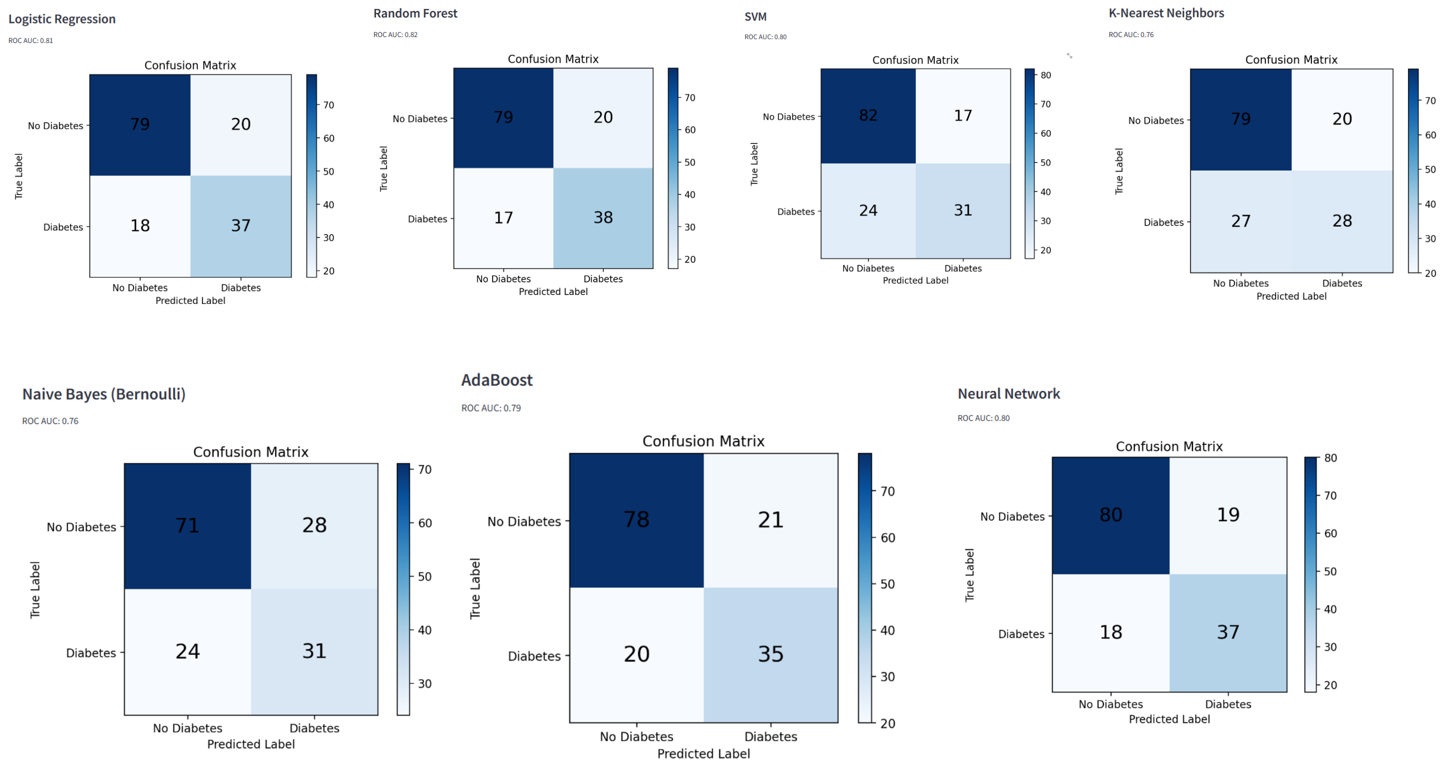
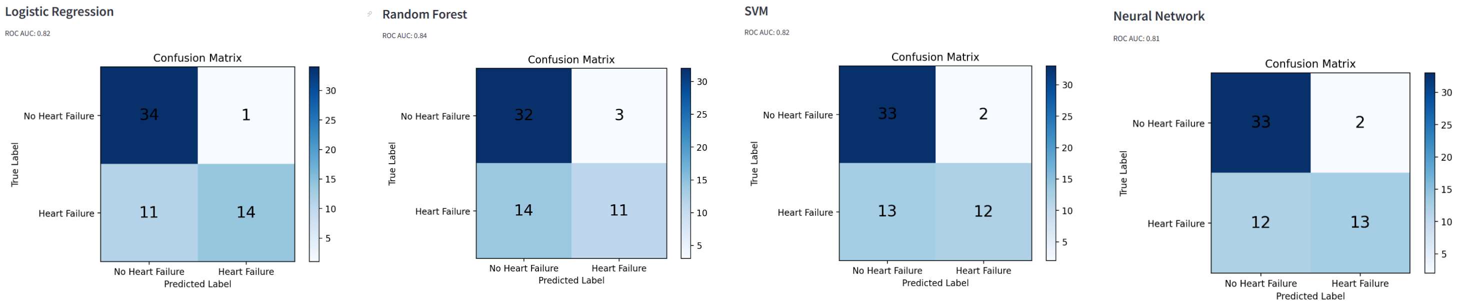


Fig 17: Heart Failure Dataset Confusion Matrices



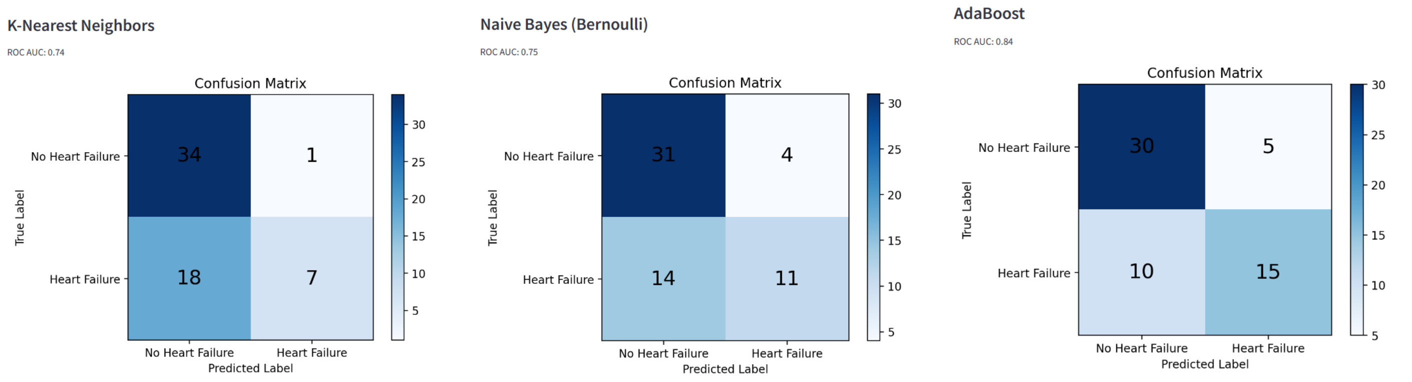
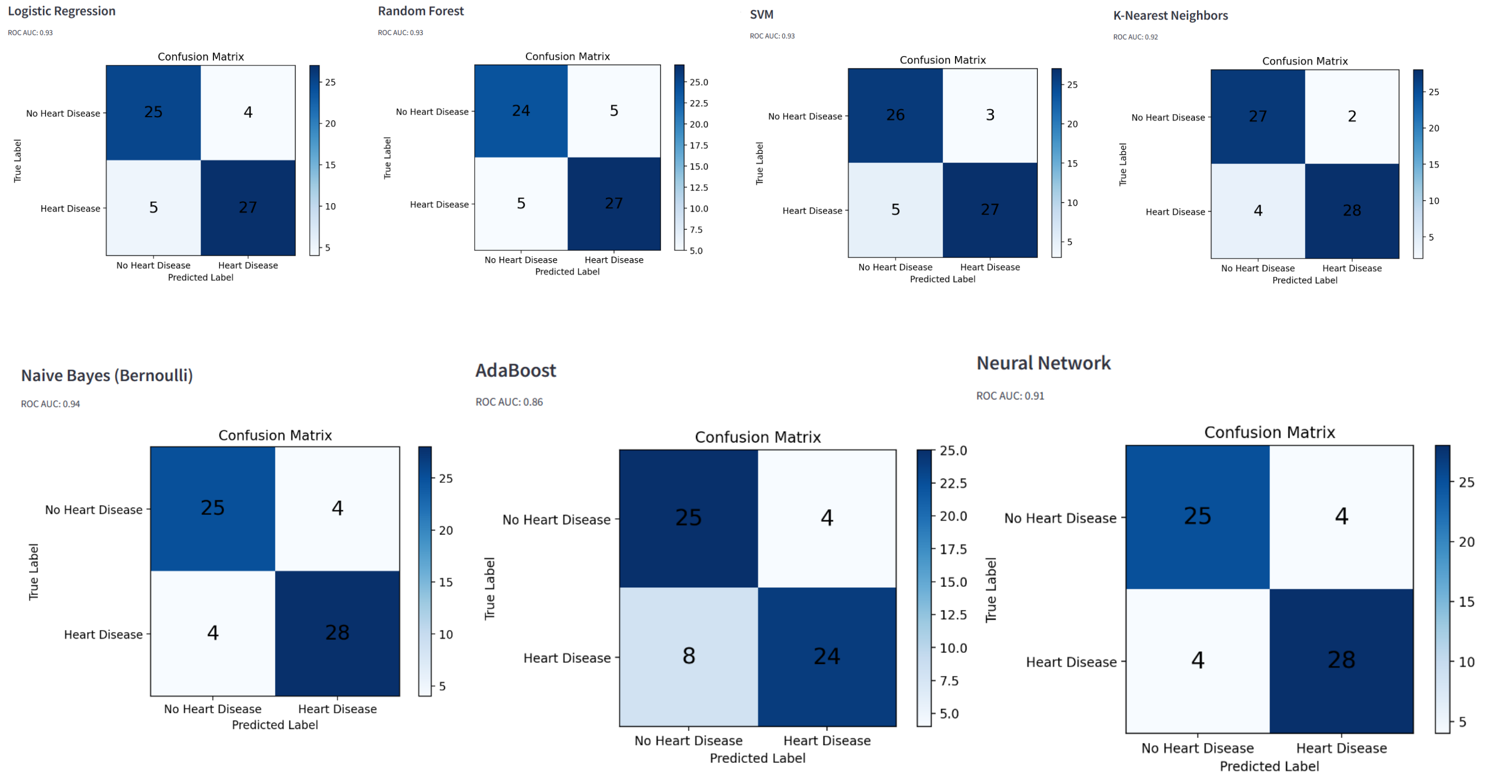


Fig 18: Heart Diseases Dataset Confusion Matrices



Learning curves provide insights into a machine learning model's training and generalisation performance. They help assess bias, variance, convergence, data sufficiency, and guide decisions related to early stopping, hyperparameter tuning, and model selection.

The following Learning Curves were obtained:

Fig 19: Mendeley’s Diabetes Dataset Learning Curves

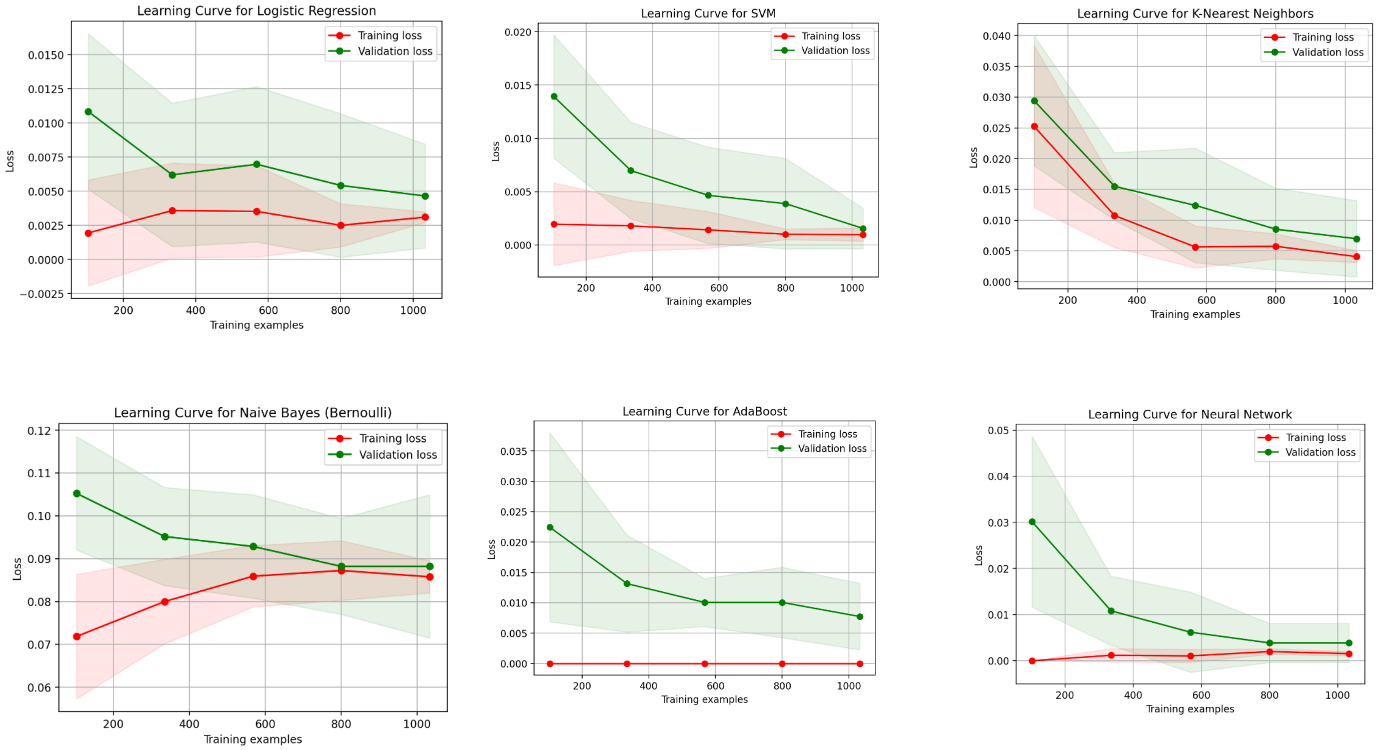
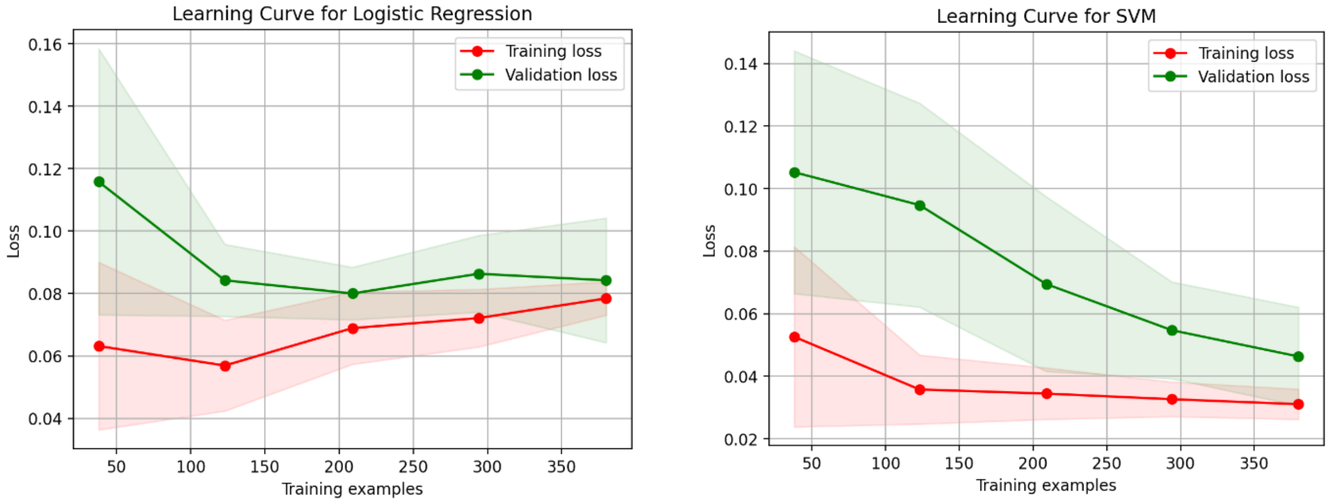


Fig 20: Pima Indians Diabetes Dataset Learning Curves



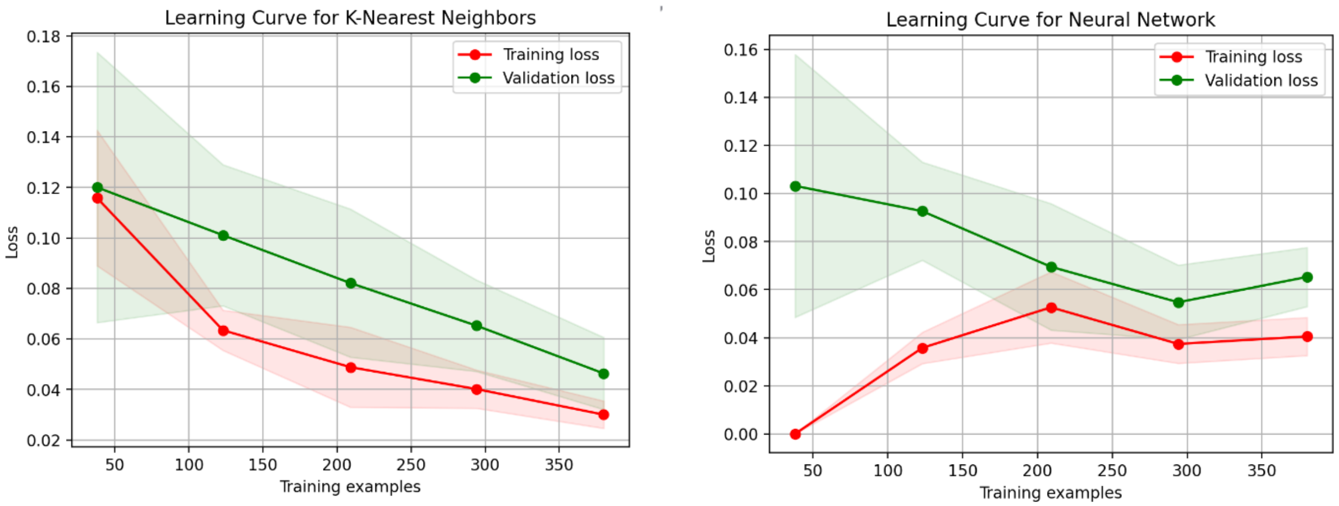


Fig 21: Heart Failure Dataset Learning Curves

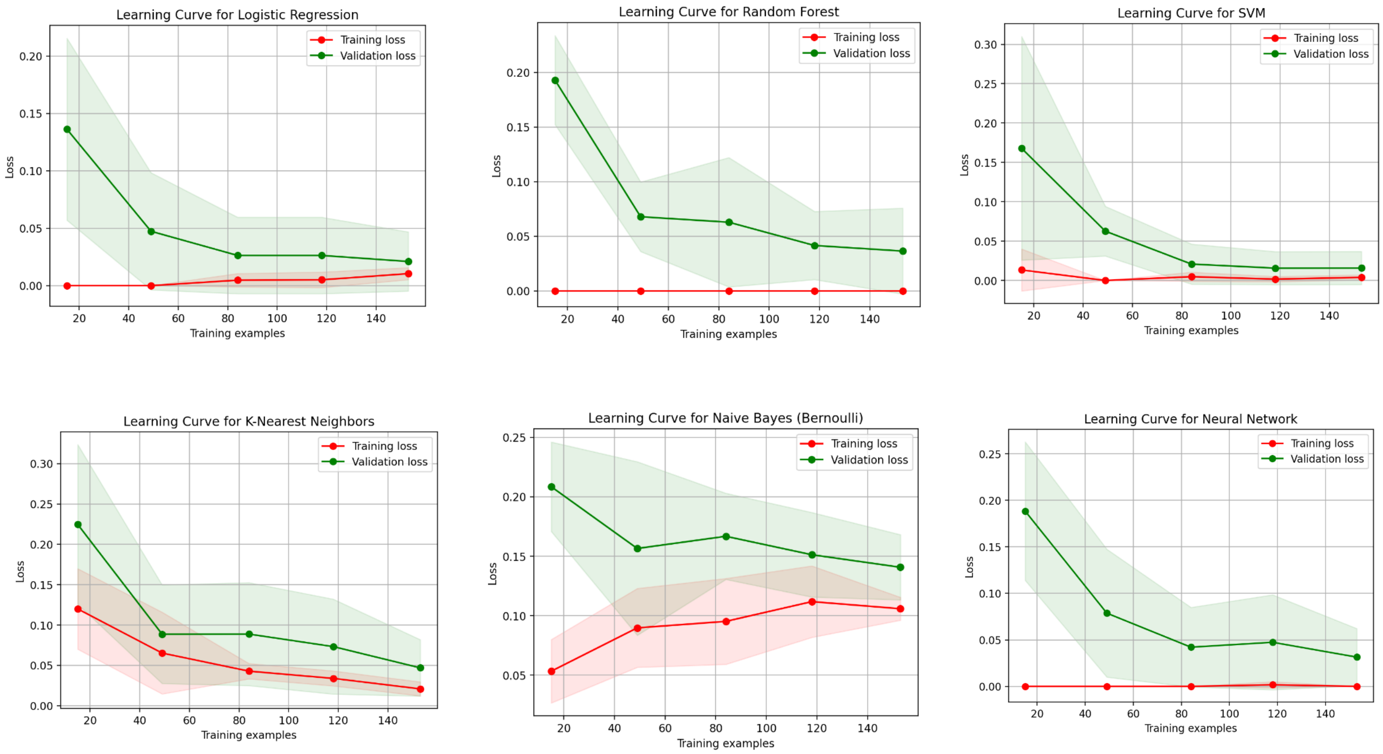
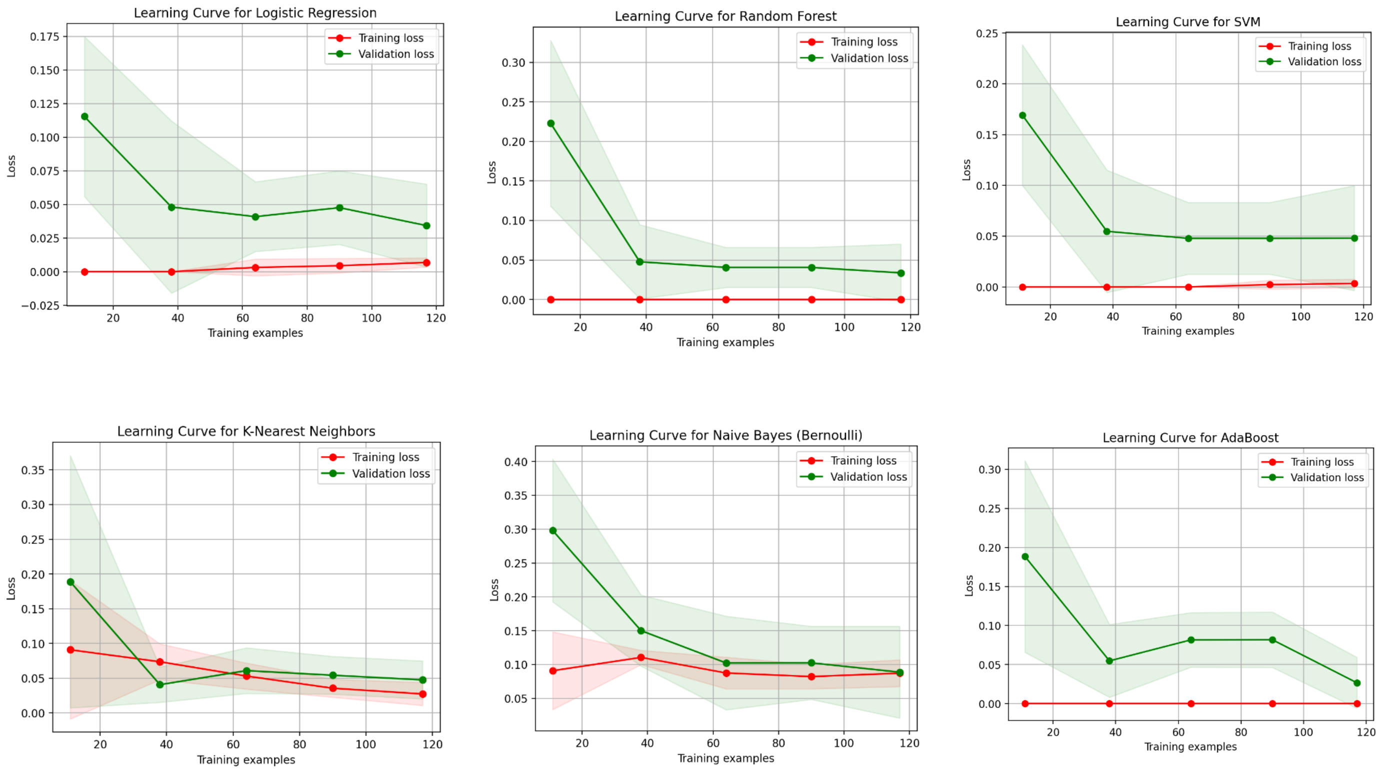


Fig 22: Heart Disease Dataset Learning Curves



Discussion and conclusion

This project delineates the seven models used in the study and makes use of them to accurately predict development of diabetes, heart failure and heart diseases' presence. The plotted graphs and charts depict that the models were adequately trained and gave good accuracy. SVM, logistic regression, neural networks and KNN outperformed other models used.
The evaluation of the first dataset shows signs of overfitting as the accuracy is very high, that is, instead of having the model learning from the dataset and being able to generalise it, the model seems to have learnt the dataset and its outcomes.

However, in the other datasets, the models have a good accuracy overall and keep varying from between the 80s and 90s percentage range.

Future research projects will be conducted in a similar manner but with implementation of combinations of models using ensemble methods, hyperparameter tuning, clustering and feature selection to work upon the prediction performance in this domain in addition to rectifying possibilities of overfitting of data.