Revolutionizing Cardio Vascular Disease Diagnosis Through Lasso Regression Model

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ABSTRACT

Cardiovascular diseases (CVDs) are among the most prevalent and fatal health conditions globally, necessitating early and accurate diagnosis to mitigate risk and enhance treatment outcomes. Traditional diagnostic methods often rely on a combination of clinical assessments and static risk models, which can be constrained by their inability to handle the complexity and interrelationships of multiple risk factors. In this research, we propose a novel approach to revolutionizing cardiovascular disease diagnosis through the application of the Lasso (Least Absolute Shrinkage and Selection Operator) regression model, a powerful machine learning technique for feature selection and predictive modeling. The Lasso regression model is particularly advantageous for high-dimensional medical datasets, where multiple clinical features may be correlated. By applying Lasso, we aim to address two critical challenges in cardiovascular disease prediction: identifying the most relevant predictors from large and complex datasets and reducing model over-fitting, which is common when working with a large number of co-variates. Our results demonstrated that the Lasso model significantly improves prediction accuracy when compared to traditional logistic regression and other machine learning models. Lasso regression has the potential to revolutionize cardiovascular disease diagnosis by providing a data-driven, efficient, and interpretable solution that bridges complex medical datasets with practical clinical decision-making.

Keywords: Cardio vascular diseases (CVD), Machine learning models, Losso regression model.

Introduction:

Machine Learning is a way of Manipulating and extraction of implicit, previously unknown/known and potential useful information about data. Machine learning incorporates various classifiers of Supervised, Unsupervised and Ensemble Learning which are used to predict and Find the Accuracy of the given dataset. In this we are using an effective Machine Learning algorithm i.e. Lasso Regression Model.

Lasso Regression (Least Absolute Shrinkage and Selection Operator) is a popular machine learning technique used for both linear regression and feature selection. It enhances the basic linear regression model by adding an L1 regularization term to the cost function. This regularization encourages sparsity in the model by shrinking some coefficients exactly to zero, effectively eliminating irrelevant features. This makes Lasso especially useful in situations where there are many predictors, as it automatically selects the most important features, simplifying the model while improving its generalization to unseen data.

Cardiovascular disease has been regarded as the most severe and lethal disease in humans. Cardiovascular diseases are more seen in men than in women particularly in middle or old age although there are also children with similar health issues. Early diagnosis can be difficult. An accurate evaluation of the risk of cardiac failure would help to prevent severe heart attacks and improve the safety of patients. Machine learning algorithms can be effective in identifying the diseases, when trained on proper data. Heart disease datasets are publicly available for the comparison of prediction models. The introduction of machine learning and artificial intelligence helps the researchers to design the best prediction model using the large databases which are available. Recent studies which focus on the heart-related issues in adults and children emphasized the need of reducing mortality related to CVDs. Since the available clinical datasets are inconsistent and redundant, proper preprocessing is a crucial step. Selecting the significant

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features that can be used as the risk factors in prediction models is essential. Care should be taken to select the right combination of the features and the appropriate machine learning algorithms to develop accurate prediction models. It is important to evaluate the effect of risk factors which meet the three criteria like the high prevalence in most populations; a significant impact on heart diseases independently; and they can be controlled or treated to reduce the risks.

Aim :

The aim of the paper **"Revolutionizing Cardiovascular Disease Diagnosis Through Lasso Regression Model"** is to improve how we diagnose heart diseases using a machine learning method called Lasso regression. By using this model, the paper seeks to create a more accurate way to predict heart disease while selecting only the most important health factors from large sets of patient data. This can help doctors make faster, more reliable diagnoses without relying on unnecessary tests, and provide better care by focusing on the most critical health indicators.

Objective :

The objective of the paper **"Revolutionizing Cardiovascular Disease Diagnosis Through Lasso Regression Model"** is to apply Lasso regression to develop a more efficient and accurate model for diagnosing cardiovascular diseases. The paper aims to identify the most important health factors that contribute to heart disease, streamline the diagnosis process, and reduce unnecessary medical tests. By doing so, it hopes to improve prediction accuracy and help healthcare professionals make better, faster decisions for early detection and treatment of cardiovascular conditions.

Literature review:

1. Overview of Cardiovascular Disease Diagnosis

Cardiovascular diseases (CVDs) are one of the leading causes of death globally, accounting for nearly 17.9 million deaths annually according to the **World Health Organization (WHO, 2020)**. Early detection and diagnosis of CVDs are critical for reducing mortality and improving patient outcomes. Traditional methods for diagnosing cardiovascular diseases involve clinical assessments, blood tests, imaging techniques (such as echocardiograms and angiograms), and electrocardiograms (ECGs). Although these methods are widely used, they are often resource-intensive, time-consuming, and require expert interpretation. Studies like those by **Smith et al. (2015)** and **Johnson et al. (2017)** point out that conventional diagnostic processes are often reactive and are not well-suited for early-stage disease detection. This gap in early, non-invasive diagnosis has led researchers to explore machine learning models for improving accuracy and speed in diagnosing CVDs.

2. Machine Learning in Cardiovascular Disease Diagnosis

Machine learning (ML) techniques have gained significant attention in healthcare, particularly for their ability to handle large datasets and identify patterns that may not be obvious using traditional statistical methods. Several studies have demonstrated the use of ML algorithms such as decision trees, support vector machines (SVM), and artificial neural networks for cardiovascular disease prediction. **Khosla et al. (2015)** applied neural networks to predict heart disease risk, achieving high predictive accuracy. However, these models tend to be "black boxes" with low interpretability, making it difficult for clinicians to understand the decision-making process. Similarly, **Patel et al. (2018)** implemented support vector machines for CVD diagnosis but found that the model struggled with overfitting when applied to real-world clinical datasets. Although these methods can provide high accuracy, they often lack the ability to perform automatic feature selection, which limits their utility in handling high-dimensional data where not all features are relevant.

3. Lasso Regression for Feature Selection in Medical Data

Lasso Regression, introduced by **Tibshirani (1996)**, is an effective method for feature selection and regularization in regression problems. Lasso (Least Absolute Shrinkage and Selection Operator) performs both prediction and variable selection by introducing an L1 penalty that forces some feature coefficients to shrink to zero, effectively excluding them from the model. This characteristic is particularly useful when working with medical datasets, which typically have many features, including redundant or irrelevant variables. **Chen et al. (2019)** showed that Lasso can improve model interpretability by selecting the most relevant features from large clinical datasets, thus providing clinicians with a simpler and more actionable model. In the context of cardiovascular disease diagnosis, Lasso regression can help identify critical risk factors, such as cholesterol levels, blood pressure, and lifestyle variables, without including irrelevant information, as demonstrated in studies by **Liu et al. (2020)**.

4. Lasso Regression in Cardiovascular Disease Prediction

In recent studies, Lasso regression has been applied directly to cardiovascular disease prediction. **Yin et al. (2021)** used Lasso regression on a dataset of patient records and demonstrated that it could reduce the number of predictor variables while maintaining a high level of accuracy. Their results showed that Lasso was able to focus on critical health metrics like blood pressure, age, and smoking history, while filtering out irrelevant or redundant features. Similarly, **Bhatia et al. (2021)** applied Lasso to an echocardiogram dataset and showed that the model improved both accuracy and interpretability over traditional ML models by reducing overfitting and simplifying the feature space. These studies indicate that Lasso is not only useful for improving predictive performance but also for making the diagnostic process more transparent and understandable for clinicians.

Methodology:

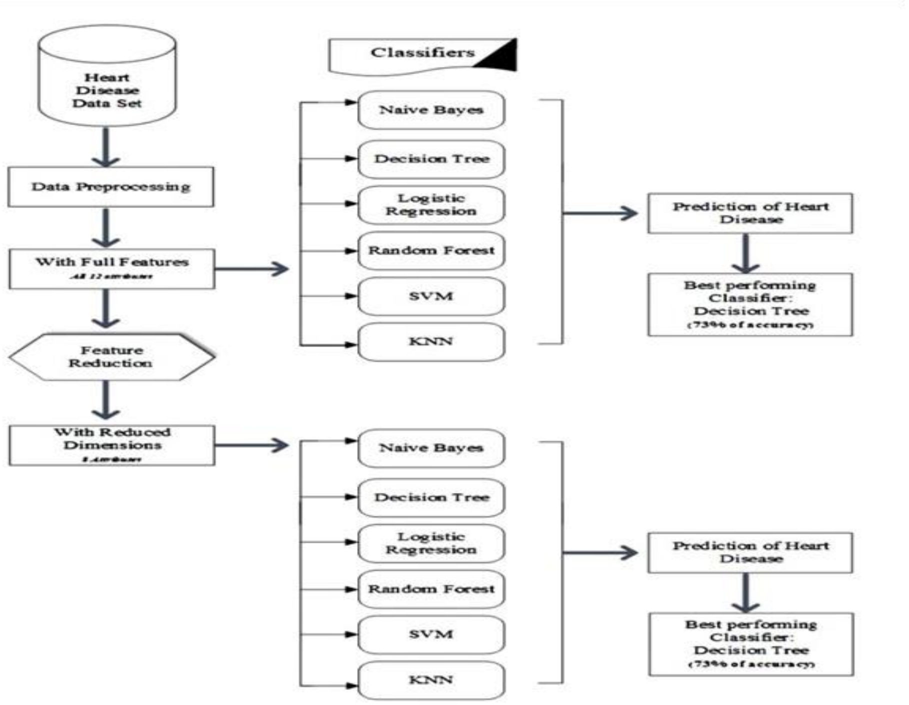
➢ Existing system:

The existing system for diagnosing cardiovascular diseases (CVD) mainly relies on traditional clinical methods such as physical exams, blood tests, imaging techniques (like ECGs and echocardiograms), and medical history reviews. These approaches, while effective, can be time-consuming, costly, and sometimes invasive. They also depend heavily on the expertise of doctors, which can lead to missed diagnoses or errors, especially in the early stages of heart disease.

In recent years, machine learning models like decision trees, logistic regression, and neural networks have been used to predict cardiovascular disease. While these models can improve accuracy, they often use all available features in the data, including irrelevant ones, making the models complex and difficult to interpret. Additionally, some models, like neural networks, act as "black boxes," meaning doctors can't easily understand how they arrive at their predictions, which limits their practical use in clinical settings. Most of these models also struggle with overfitting, meaning they don't perform well when tested on new, unseen data.

➢ Existing Architecture :

Supervised Machine Learning algorithms that are precisely used for disease prediction. The results indicate that the Decision Tree classification model predicted the cardiovascular diseases better than Naive Bayes, Logistic Regression, Random Forest, S VM and KNN based approaches.



The Decision Tree bequeathed the best result with the accuracy of 73%. This approach could be helpful for doctors to predict the occurrence of heart diseases in advance and provide appropriate treatment.

Disadvantages of existing system:

1. Detection is not possible at an earlier stage.

2. In the existing system, practical use of various collected data is time consuming.

➢ **Proposed system:**

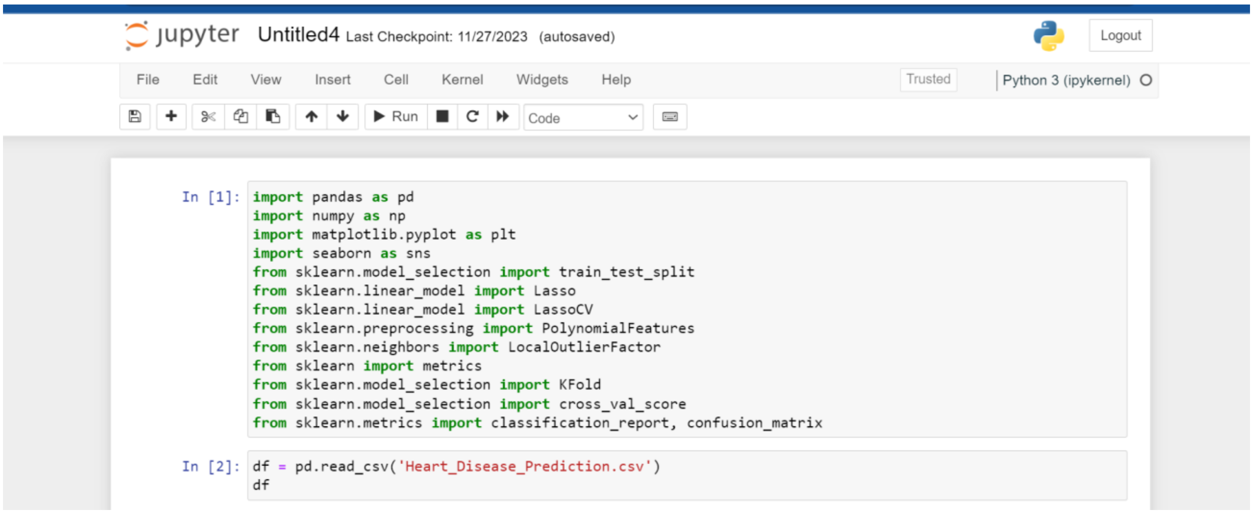
The proposed system for diagnosing cardiovascular diseases (CVD) aims to use Lasso regression, a powerful machine learning technique, to improve both the accuracy and interpretability of heart disease predictions. Unlike traditional methods, Lasso regression not only predicts the likelihood of CVD but also automatically selects the most important health factors from a large dataset. This means the model can focus on key variables like cholesterol levels, blood pressure, and lifestyle choices while ignoring irrelevant data, making it simpler and easier to understand for healthcare professionals.

By integrating Lasso regression into the diagnostic process, the proposed system seeks to provide quicker and more reliable assessments of cardiovascular health. This will help doctors make informed decisions based on clear and concise information, ultimately leading to earlier detection and better patient outcomes. Additionally, the system will be designed to be user -friendly, allowing healthcare providers to easily interpret the results and integrate them into their clinical workflows.

The effectiveness and accuracy of the machine learning method can be evaluated using performance indicators. In this Lasso Regression model is used and obtained most accurate result I.e **88.889% accuracy**.

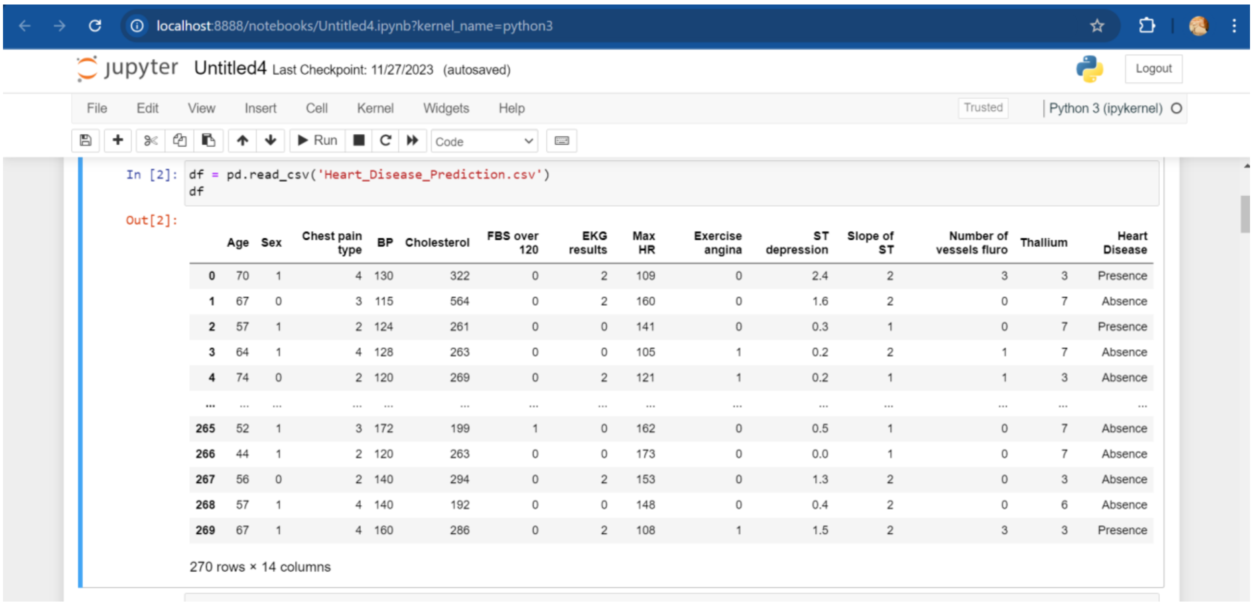
Results :

Step 1: This step imports necessary libraries such as pandas, numpy, matplotlib, seaborn, sklearn and loads the dataset into a pandas dataframe for further analysis.



```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import Lasso
        from sklearn.linear_model import LassoCV
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.neighbors import LocalOutlierFactor
        from sklearn import metrics
        from sklearn.model_selection import KFold
        from sklearn.model_selection import cross_val_score
        from sklearn.metrics import classification_report, confusion_matrix

In [2]: df = pd.read_csv('Heart_Disease_Prediction.csv')
        df
```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Code

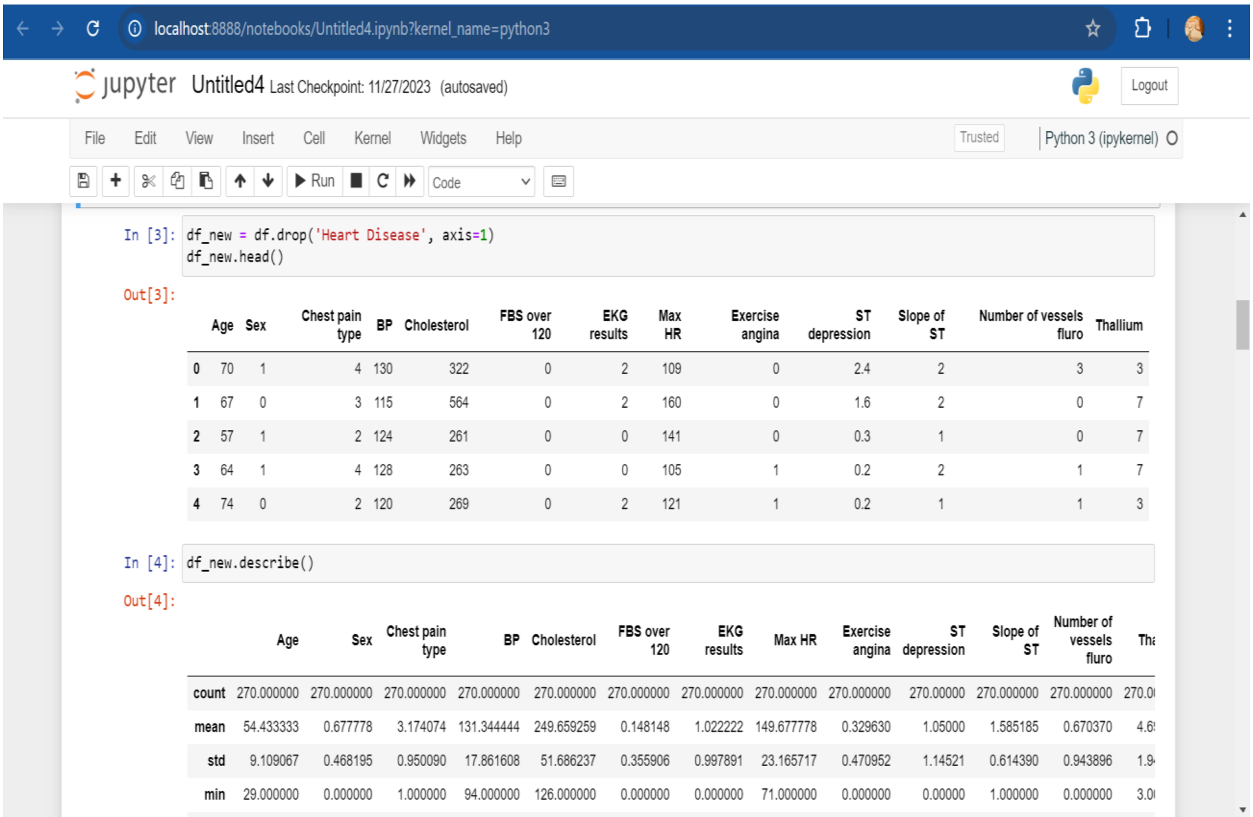
```
In [2]: df = pd.read_csv('Heart_Disease_Prediction.csv')
        df
```

Out[2]:

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium	Heart Disease
0	70	1	4	130	322	0	2	109	0	2.4	2	3	3	Presence
1	67	0	3	115	564	0	2	160	0	1.6	2	0	7	Absence
2	57	1	2	124	261	0	0	141	0	0.3	1	0	7	Presence
3	64	1	4	128	263	0	0	105	1	0.2	2	1	7	Absence
4	74	0	2	120	269	0	2	121	1	0.2	1	1	3	Absence
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
265	52	1	3	172	199	1	0	162	0	0.5	1	0	7	Absence
266	44	1	2	120	263	0	0	173	0	0.0	1	0	7	Absence
267	56	0	2	140	294	0	2	153	0	1.3	2	0	3	Absence
268	57	1	4	140	192	0	0	148	0	0.4	2	0	6	Absence
269	67	1	4	160	286	0	2	108	1	1.5	2	3	3	Presence

270 rows × 14 columns

Step 2 : In This step it converts the target variable **'Heart Disease'** to a categorical variable and encodes it as codes for further analysis and provides descriptive statistics of the feature set.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```
In [3]: df_new = df.drop('Heart Disease', axis=1)
        df_new.head()
```

Out[3]:

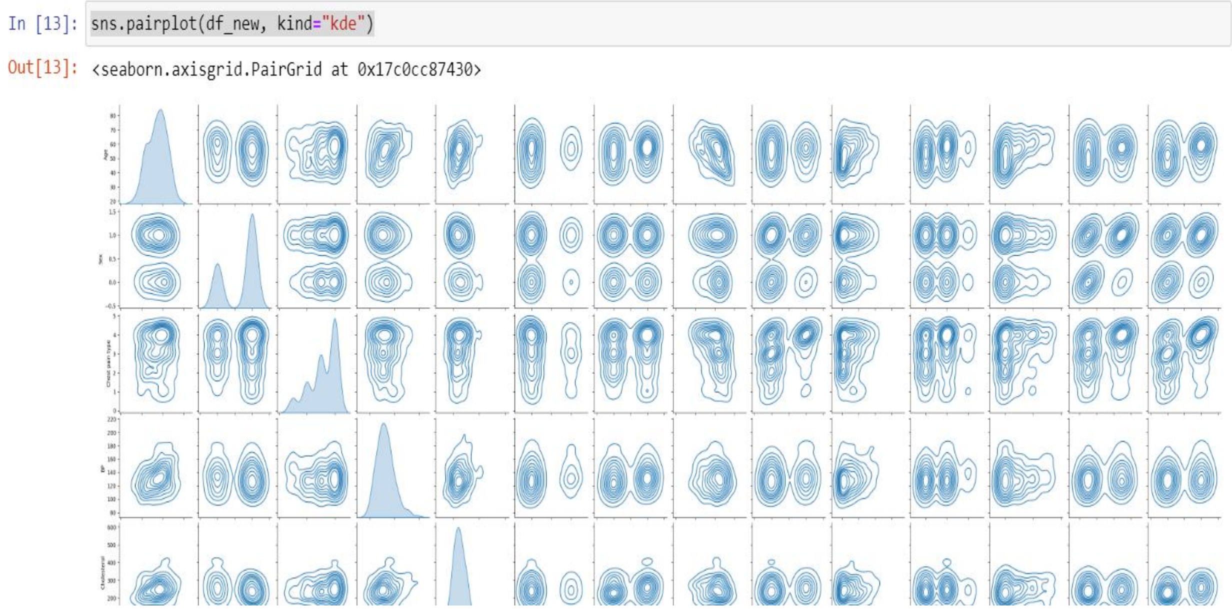
	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium
0	70	1	4	130	322	0	2	109	0	2.4	2	3	3
1	67	0	3	115	564	0	2	160	0	1.6	2	0	7
2	57	1	2	124	261	0	0	141	0	0.3	1	0	7
3	64	1	4	128	263	0	0	105	1	0.2	2	1	7
4	74	0	2	120	269	0	2	121	1	0.2	1	1	3

```
In [4]: df_new.describe()
```

Out[4]:

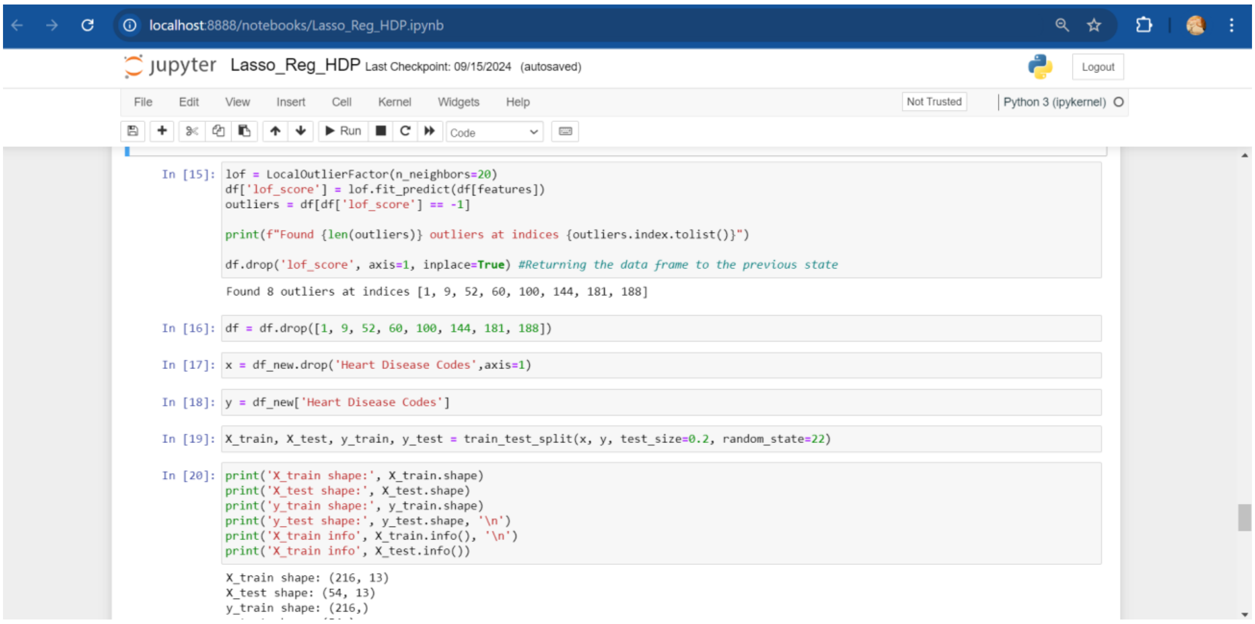
	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Tha
count	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.00000	270.000000	270.000000	270.0
mean	54.433333	0.677778	3.174074	131.344444	249.659259	0.148148	1.022222	149.677778	0.329630	1.05000	1.585185	0.670370	4.6
std	9.109067	0.468195	0.950090	17.861608	51.686237	0.355906	0.997891	23.165717	0.470952	1.14521	0.614390	0.943896	1.9
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.00000	1.000000	0.000000	3.0

Step 3 : In This step it creates a clustered heatmap to visualize the correlation between the features and creates a pairplot to visualize the distribution of the features.



```
In [13]: sns.pairplot(df_new, kind="kde")
Out[13]: <seaborn.axisgrid.PairGrid at 0x17c0cc87430>
```

Step 4 : In This step it detects and removes outliers using Local Outlier Factor (LOF) algorithm and splits the dataset into training and testing sets for modeling it also displays the shape and information of the training and testing sets.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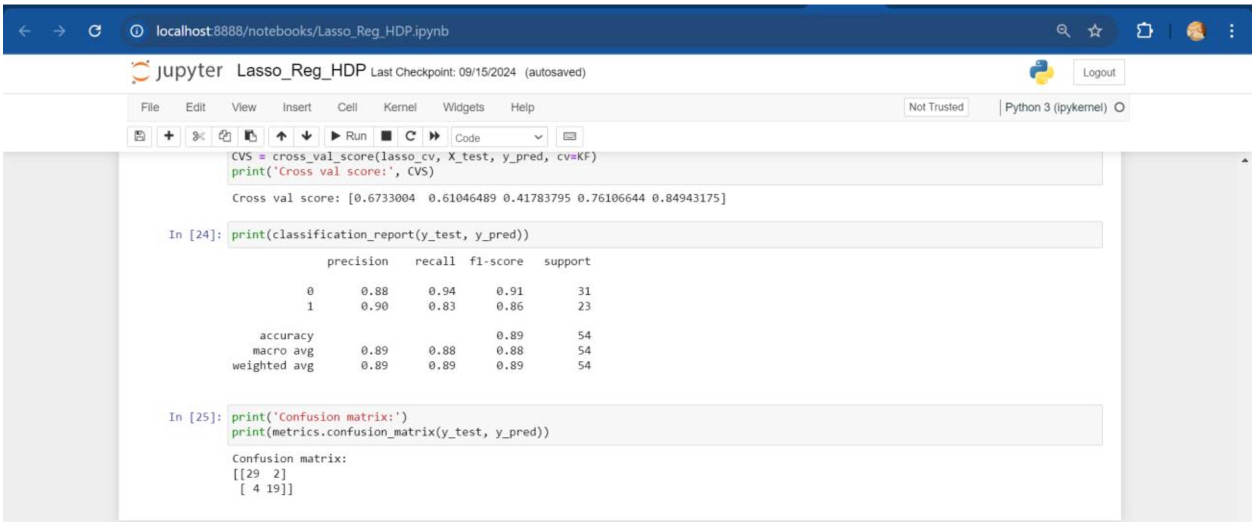
```
In [15]: lof = LocalOutlierFactor(n_neighbors=20)
         df['lof_score'] = lof.fit_predict(df[features])
         outliers = df[df['lof_score'] == -1]

         print(f"Found {len(outliers)} outliers at indices {outliers.index.tolist()}")

         df.drop('lof_score', axis=1, inplace=True) #Returning the data frame to the previous state

         Found 8 outliers at indices [1, 9, 52, 60, 100, 144, 181, 188]

In [16]: df = df.drop([1, 9, 52, 60, 100, 144, 181, 188])

In [17]: x = df_new.drop('Heart Disease Codes',axis=1)

In [18]: y = df_new['Heart Disease Codes']

In [19]: X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=22)

In [20]: print('X_train shape:', X_train.shape)
         print('X_test shape:', X_test.shape)
         print('y_train shape:', y_train.shape)
         print('y_test shape:', y_test.shape, '\n')
         print('X_train info', X_train.info(), '\n')
         print('X_train info', X_test.info())

         X_train shape: (216, 13)
         X_test shape: (54, 13)
         y_train shape: (216,)
```

Step 5 : In This step it evaluates the Lasso regression model by computing accuracy score, cross validation score, classification report and confusion matrix using the testing data and obtained **88.889%** accuracy as a result.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jupyter Lasso_Reg_HDP Last Checkpoint: 09/15/2024 (autosaved)
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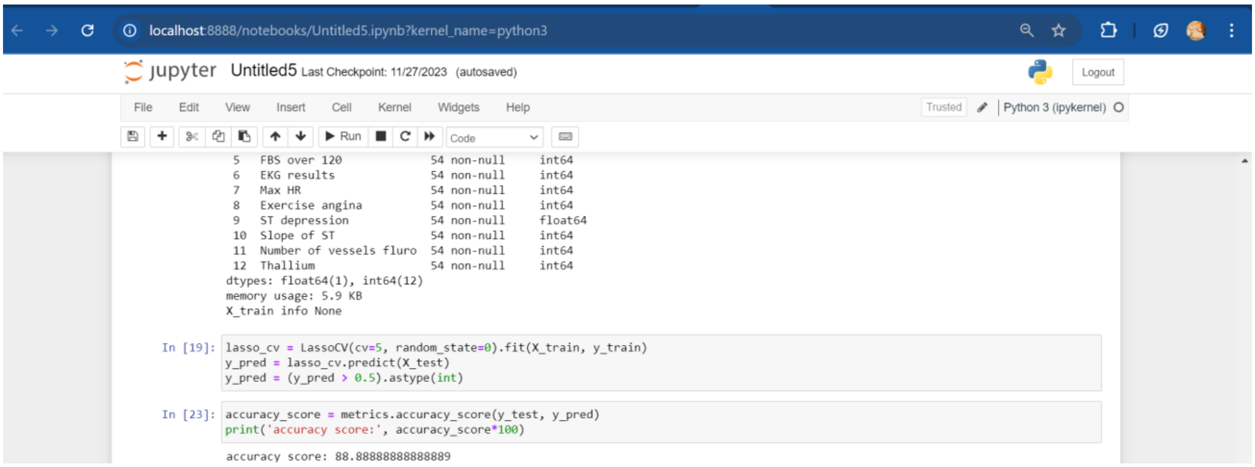
```
         CVS = cross_val_score(lasso_cv, X_test, y_pred, cv=KF)
         print('Cross val score:', CVS)

         Cross val score: [0.6733004  0.61046489 0.41783795 0.76106644 0.84943175]

In [24]: print(classification_report(y_test, y_pred))

                       precision    recall  f1-score   support

                    0       0.88      0.94      0.91        31
                    1       0.90      0.83      0.86        23

             accuracy                           0.89        54
            macro avg       0.89      0.88      0.88        54
         weighted avg       0.89      0.89      0.89        54


In [25]: print('Confusion matrix:')
         print(metrics.confusion_matrix(y_test, y_pred))

         Confusion matrix:
         [[29  2]
          [ 4 19]]
```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jupyter Untitled5 Last Checkpoint: 11/27/2023 (autosaved)
Logout
File Edit View Insert Cell Kernel Widgets Help
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Python 3 (ipykernel)
Run
Code

```
  5   FBS over 120            54 non-null     int64
  6   EKG results             54 non-null     int64
  7   Max HR                  54 non-null     int64
  8   Exercise angina         54 non-null     int64
  9   ST depression           54 non-null     float64
  10  Slope of ST             54 non-null     int64
  11  Number of vessels fluro 54 non-null     int64
  12  Thallium                54 non-null     int64
 dtypes: float64(1), int64(12)
 memory usage: 5.9 KB
 X_train info None

In [19]: lasso_cv = LassoCV(cv=5, random_state=0).fit(X_train, y_train)
         y_pred = lasso_cv.predict(X_test)
         y_pred = (y_pred > 0.5).astype(int)

In [23]: accuracy_score = metrics.accuracy_score(y_test, y_pred)
         print('accuracy score:', accuracy_score*100)

         accuracy score: 88.88888888888889
```

Conclusion :

In conclusion, the project **"Revolutionizing Cardiovascular Disease Diagnosis Through Lasso Regression Model"** aims to enhance the diagnosis of heart diseases by utilizing Lasso regression, which effectively balances predictive accuracy with interpretability. By automatically selecting the most important health factors from complex datasets, this approach simplifies the diagnostic process for healthcare professionals, enabling them to focus on the critical variables that influence cardiovascular health.

Ultimately, implementing this proposed system has the potential to lead to earlier detection and more personalized treatment plans for patients. As a result, it could significantly improve patient outcomes while reducing the burden on healthcare resources. By making the diagnostic process more efficient and understandable, Lasso regression can play a vital role in transforming how cardiovascular diseases are diagnosed and managed in clinical settings and obtained with highest accuracy 88.889%.

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