MACHINE LEARNING

UNLOCKING INSIGHTS FOR HEART FAILURE PREDICTION

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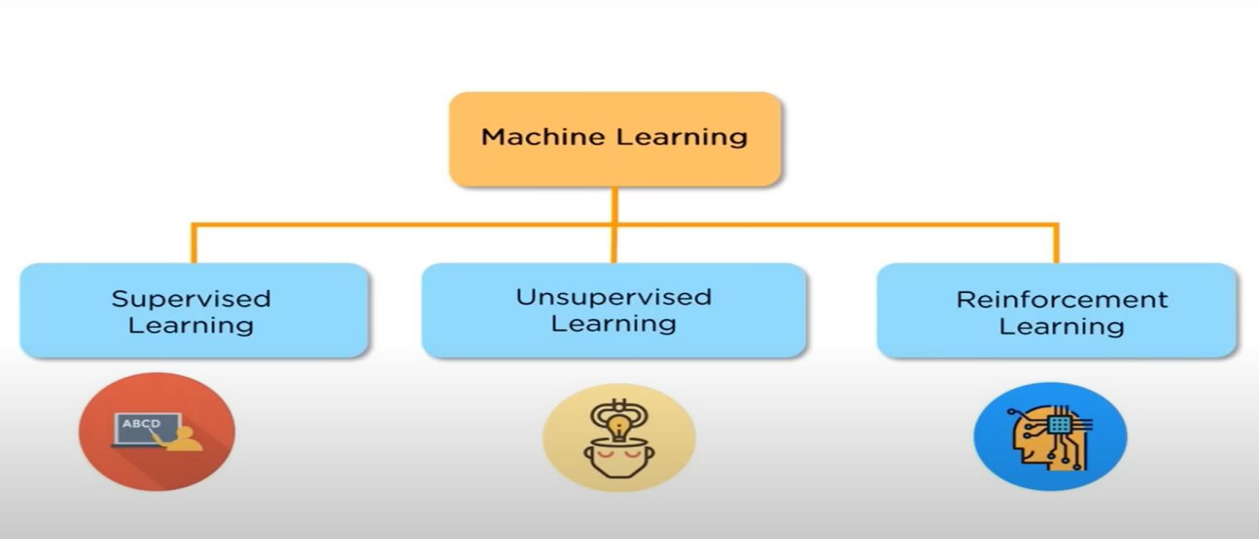
What is machine learning?

Machine learning is a subset of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computers to perform tasks without being explicitly programmed. The fundamental idea behind machine learning is to allow computers to learn from data and improve their performance over time.

There are three main types of machine learning:



Supervised Learning	Unsupervised Learning	Reinforcement Learning
* Algorithms are trained on labeled datasets, where input data is paired with corresponding output labels. * Classification (assigning labels) and regression (predicting continuous output). * In the real-world, supervised learning can be used for Risk Assessment, Image classification, Fraud Detection, spam filtering.	* Algorithms operate on unlabeled data to inherent patterns or structures. * Clustering (grouping similar data points) and dimensionality reduction. * In the real-world, un-supervised learning can be used for Customer Segmentation, Principal Component Analysis (PCA), Anomaly Detection.	* An agent learns decision-making by interacting with an environment, receiving feedback in the form of rewards or penalties. * Learn a strategy or policy maximizing cumulative rewards over time. * Game Playing – AlphaGo, Robotics - Autonomous Navigation, Recommendation Systems.

🚀 Let Us Dive into an Experiment: Predicting Heart Failure with Machine Learning! 🚀

To unravel patterns within the "heart_failure_clinical_records_dataset.csv" and revolutionize predictive insights in cardiovascular health.

Experiment Overview:

🔍 **Dataset Exploration**:

Uncover the hidden gems within the clinical records dataset, featuring patient information, medical history, and health metrics.

🤖 **Algorithms on Stage:**

Support Vector Machines (SVM): The precision of hyperplanes!

Logistic Regression: Unleashing logistic functions for probability modeling!

Decision Tree Classifier: Navigating data with tree structures!

Random Forest Classifier: Resembling the power of decision trees!

K-Nearest Neighbors (KNN): Connecting predictions based on proximity!

Let the Experiment Begin....

Methodology:

- **Data Preprocessing:**
  - Addressed missing values.
  - Standardized or normalized numerical features.
  - One-hot encoded categorical variables.
- **Splitting Data:**
  - 80% for training, 20% for testing.
- **Model Training:**
  - Each algorithm trained on the training set.
- **Performance Evaluation:**
  - Metrics used: Precision, Recall, Accuracy.
    Evaluated models on the test set

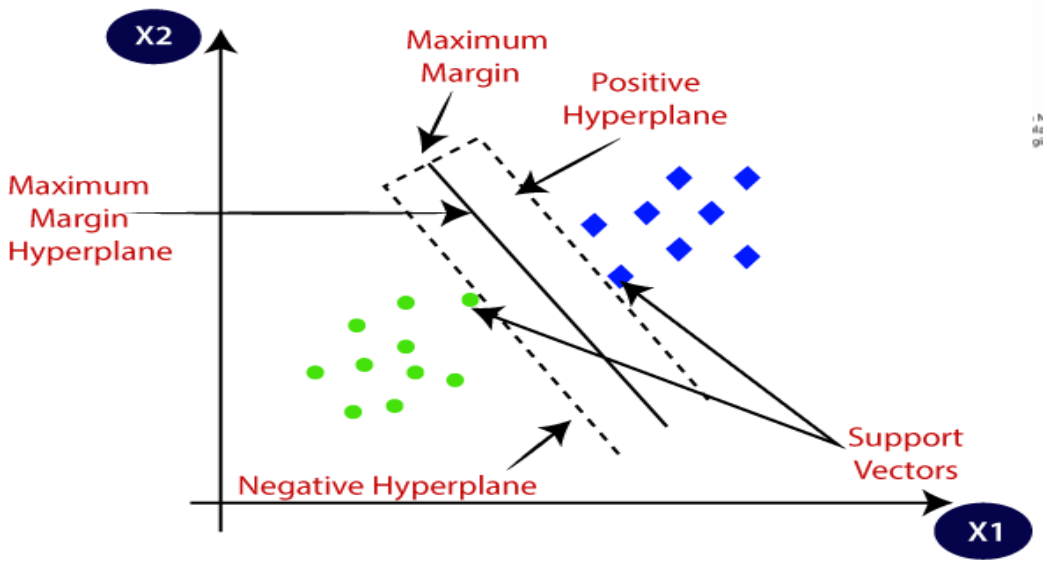
Stay Tuned for Results --->

Support Vector Machines (SVM)

Support Vector Machines (SVM) are supervised learning algorithms used for classification and regression tasks, particularly effective when dealing with non-linearly separable data.

Key Concepts:

- **Hyperplane:**
  - SVM identifies the optimal hyperplane that maximizes the margin between classes in the feature space.
  - Especially useful for scenarios where linear separation is not feasible.
- **Kernel Trick:**
  - SVM employs the kernel trick to handle non-linear relationships in data by mapping it into a higher-dimensional space.
  - Enables SVM to capture complex patterns and make accurate predictions.
- **Support Vectors:**
  - Support vectors are the data points closest to the hyperplane.
  - They play a pivotal role in determining the position and orientation of the optimal hyperplane.
- **C Parameter:**
  - A smaller C creates a larger margin but may allow for some misclassifications, while a larger C results in a smaller margin with fewer misclassifications.



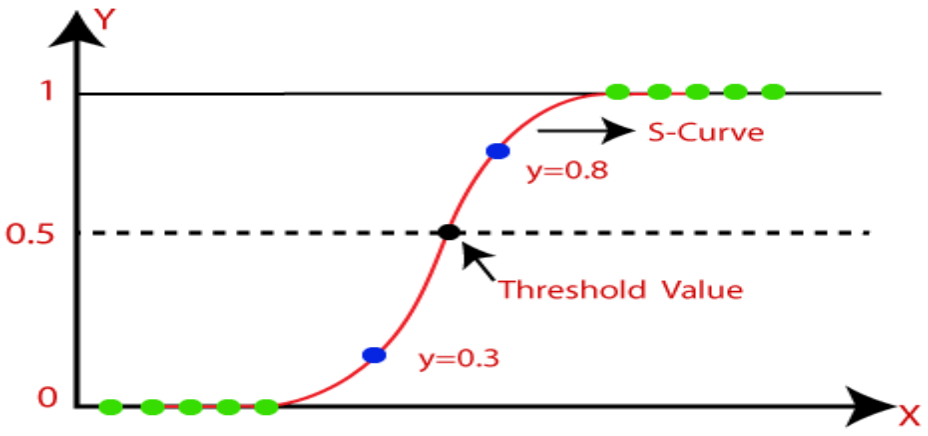
Logistic Regression

Logistic Regression is a widely used supervised learning algorithm for binary and multi-class classification tasks. Despite its name, it is used for classification, not regression. Logistic Regression models the probability that a given input belongs to a particular class.

- **Multi-class Logistic Regression:**
  Extends the binary logistic regression to handle multiple classes using techniques like one-vs-rest.

Key Concepts:

- **Sigmoid Function:**
  - Logistic Regression uses the sigmoid (logistic) function to map any real-valued number to the range [0, 1].
  - The sigmoid function ensures that the output can be interpreted as probability.
- **Decision Boundary:**
  - The algorithm creates a decision boundary based on learned coefficients and features.
  - For binary classification, the decision boundary separates data points into two classes.
- **Maximum Likelihood Estimation:**
  - Logistic Regression maximizes the likelihood function to find the optimal parameters (weights) that best fit the observed data.

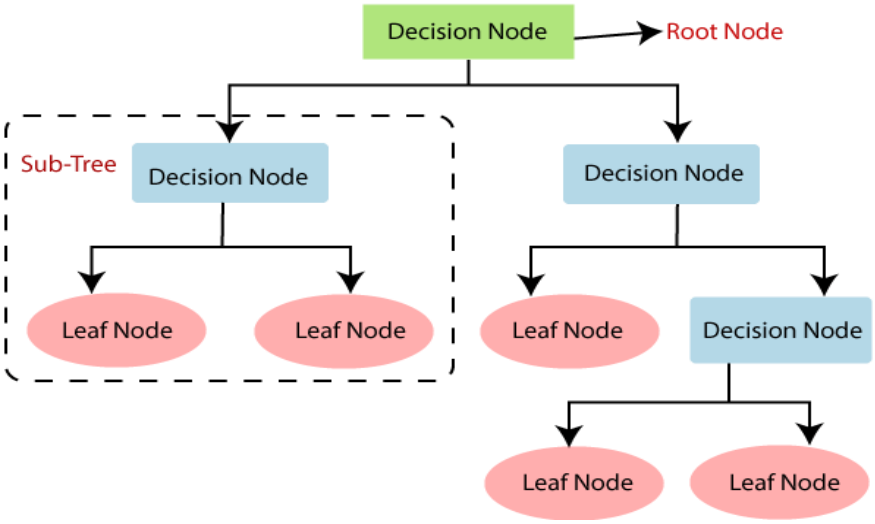


Decision Tree Classifier

A Decision Tree Classifier is a versatile supervised learning algorithm used for both classification and regression tasks. It makes decisions by recursively splitting the dataset based on feature conditions until a stopping criterion is met, forming a tree-like structure of decisions.

Key Concepts:

- **Node Splitting:**
  - The algorithm selects the most informative feature to split the data at each node.
  - The goal is to maximize information gain (for classification) or variance reduction (for regression).
- **Decision Nodes:**
  - Nodes in the tree represent decisions based on feature conditions.
  - Each decision node splits the data into subsets, guiding the traversal of the tree.
- **Leaf Nodes:**
  - Leaf nodes contain the final predicted output or class label.
  - The algorithm assigns the majority class for classification tasks or the mean value for regression tasks.
- **Entropy and Information Gain:**
  - For classification, Decision Trees use entropy to measure impurity.
  - Information gain is the reduction in entropy achieved by a split and guides the tree construction.

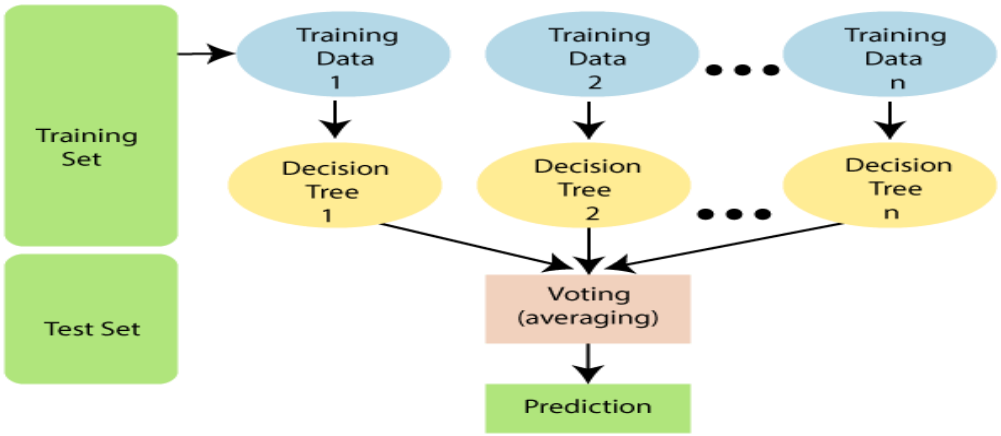


Random Forest Classifier

The Random Forest Classifier is an ensemble learning method based on Decision Trees. It constructs a multitude of Decision Trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees.

Key Concepts:

- **Ensemble of Trees:**
  - Random Forest builds multiple Decision Trees independently during training.
  - Each tree is trained on a random subset of the data, and features are randomly selected for each split.
- **Voting Mechanism:**
  - For classification tasks, the mode (most frequent class) of the predictions from individual trees is taken as the final output.
  - For regression, the mean prediction from all trees is used.
- **Bootstrap Aggregating (Bagging):**
  - Random Forest employs bagging, a technique where each tree is trained on a bootstrap sample (randomly sampled with replacement) from the original dataset.
- **Feature Randomness:**
  - At each split, a random subset of features is considered, preventing individual trees from dominating the ensemble.
  - Reduces overfitting and increases robustness.

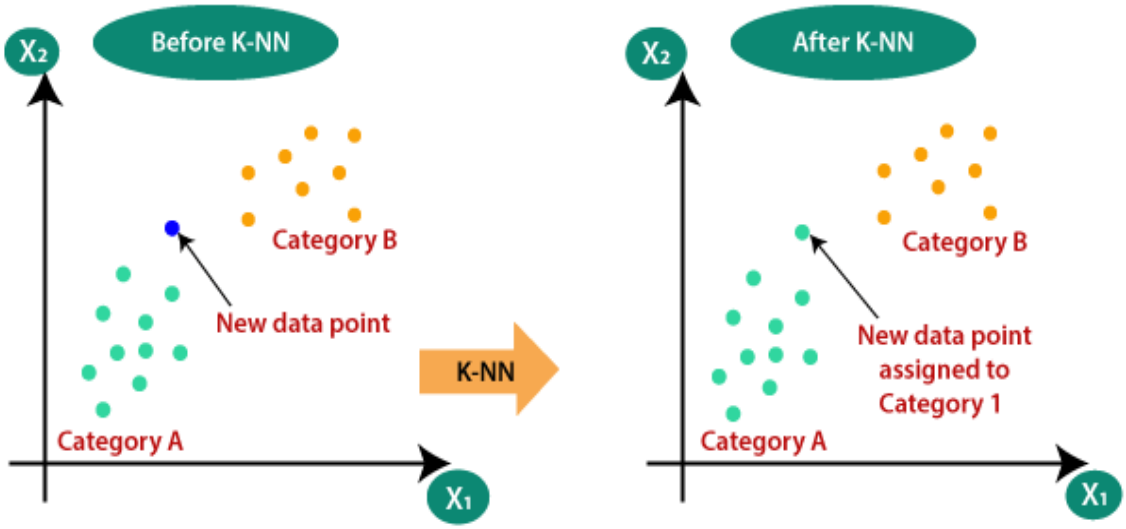


K-Nearest Neighbors (KNN) Classifier

K-Nearest Neighbors (KNN) is a simple and intuitive supervised learning algorithm used for classification and regression tasks. It makes predictions based on the majority class or average value of the k-nearest neighbors in the feature space.

Key Concepts:

- **Nearest Neighbors:**
  - KNN classifies data points based on the majority class or average value of their k-nearest neighbors in the feature space.
  - The distance metric (Euclidean, Manhattan, etc.) determines "closeness."
- **Hyperparameter 'k':**
  - 'k' represents the number of neighbors considered for classification.
  - Small 'k' values lead to more flexible models but can be sensitive to noise. Larger 'k' values provide smoother decision boundaries.
- **Decision Rule:**
  - For classification, the majority class among the neighbors determines the predicted class.
  - For regression, the average of the neighbors' values is taken.
- **Non-Parametric:**
  - KNN is a non-parametric algorithm, meaning it does not make explicit assumptions about the underlying data distribution.



Choosing the Right Algorithms for Prediction: A Strategic Decision 🌐 💡

In our mission to understand heart problems using the "heart_failure_clinical_records_dataset," we chose some Machine learning algorithms to help us out.

🔄 <------Let see some coding part------> 🚀

In [ ]:
```
# NumPy is often used for numerical operations
# Pandas is commonly used for data cleaning, analysis, and exploration with tabular data
import numpy as np
import pandas as pd
```

Loading Data

In [ ]:
```
data_df = pd.read_csv("heart_failure_clinical_records_dataset.csv") #load the dataset
data_df.head() #show the first 5 rows from the dataset
```

Out[ ]:

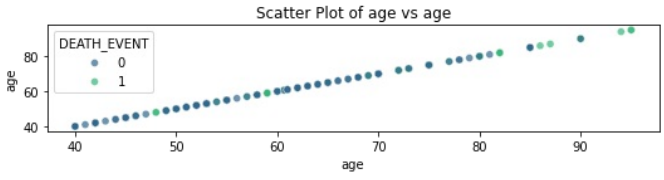
	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	se
0	75.0	0	582	0	20	1	265000.00	1.9	130	
1	55.0	0	7861	0	38	0	263358.03	1.1	136	
2	65.0	0	146	0	20	0	162000.00	1.3	129	
3	50.0	1	111	0	20	0	210000.00	1.9	137	
4	65.0	1	160	1	20	0	327000.00	2.7	116	

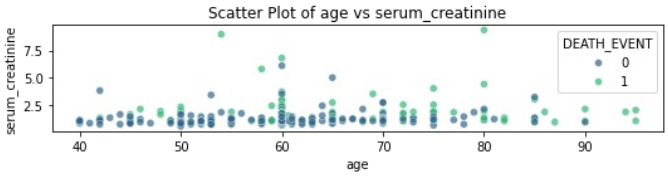
In [ ]:
```
#checking if there is any inconsistency in the dataset
#as we see there are no null values in the dataset, so the data can be processed
data_df.info()
```

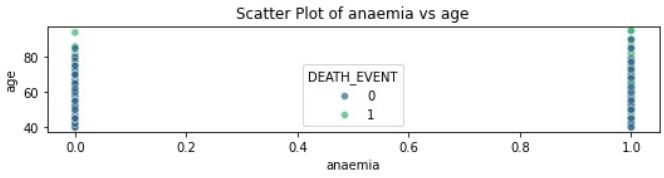
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   age                       299 non-null    float64
 1   anaemia                   299 non-null    int64  
 2   creatinine_phosphokinase  299 non-null    int64  
 3   diabetes                  299 non-null    int64  
 4   ejection_fraction         299 non-null    int64  
 5   high_blood_pressure       299 non-null    int64  
 6   platelets                 299 non-null    float64
 7   serum_creatinine          299 non-null    float64
 8   serum_sodium              299 non-null    int64  
 9   sex                       299 non-null    int64  
 10  smoking                   299 non-null    int64  
 11  time                      299 non-null    int64  
 12  DEATH_EVENT               299 non-null    int64  
dtypes: float64(3), int64(10)
memory usage: 30.5 KB
```

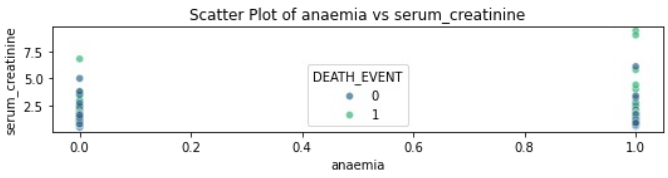
Visualizing data

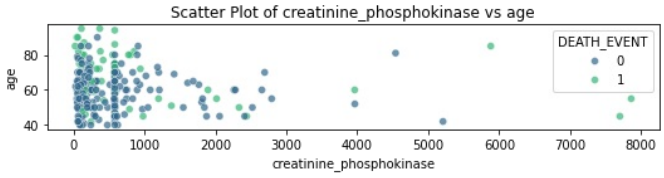
In [ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt


# Select features for the scatter plot
selected_features = ['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes', 'ejection_fraction',
 'high_blood_pressure', 'platelets', 'serum_creatinine', 'serum_sodium', 'sex', 'smoking', 'time']

# Set up subplots
fig, axes = plt.subplots(nrows=len(selected_features), ncols=2, figsize=(15, 2 * len(selected_features)))

# Plot scatter plots for each feature against 'DEATH_EVENT'
for i, feature in enumerate(selected_features):
    # Scatter plot for feature vs 'DEATH_EVENT' (0)
    sns.scatterplot(x=feature, y='age', hue='DEATH_EVENT', data=data_df, ax=axes[i, 0], palette='viridis',
                    alpha=0.7)
    axes[i, 0].set_title(f'Scatter Plot of {feature} vs age')
    axes[i, 0].set_xlabel(feature)
    axes[i, 0].set_ylabel('age')

    # Scatter plot for feature vs 'DEATH_EVENT' (1)
    sns.scatterplot(x=feature, y='serum_creatinine', hue='DEATH_EVENT', data=data_df, ax=axes[i, 1],
                    palette='viridis', alpha=0.7)
    axes[i, 1].set_title(f'Scatter Plot of {feature} vs serum_creatinine')
    axes[i, 1].set_xlabel(feature)
    axes[i, 1].set_ylabel('serum_creatinine')

# Adjust layout
plt.tight_layout()
plt.show()
```

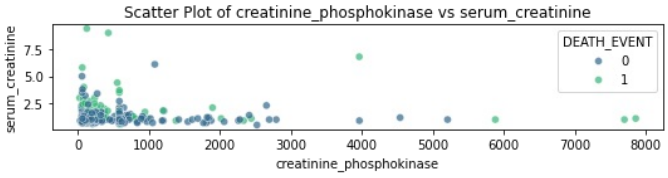

Scatter Plot of age vs age
DEATH_EVENT
0
1
age
40
60
80
40
50
60
70
80
90
age

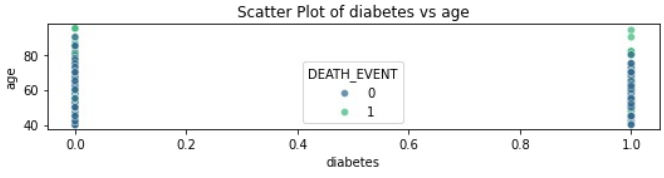

Scatter Plot of age vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
40
50
60
70
80
90
age

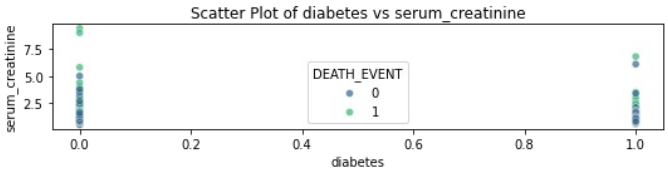

Scatter Plot of anaemia vs age
DEATH_EVENT
0
1
age
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
anaemia

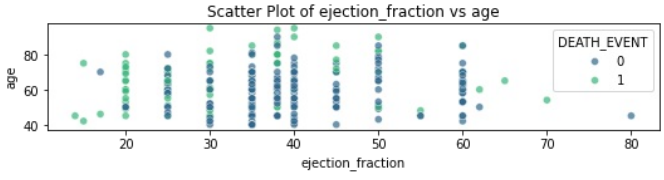

Scatter Plot of anaemia vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0.0
0.2
0.4
0.6
0.8
1.0
anaemia

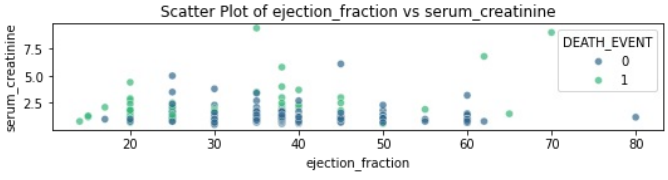

Scatter Plot of creatinine_phosphokinase vs age
DEATH_EVENT
0
1
age
40
60
80
0
1000
2000
3000
4000
5000
6000
7000
8000
creatinine_phosphokinase


Scatter Plot of creatinine_phosphokinase vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0
1000
2000
3000
4000
5000
6000
7000
8000
creatinine_phosphokinase

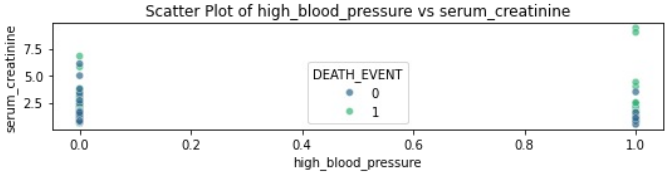

Scatter Plot of diabetes vs age
DEATH_EVENT
0
1
age
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
diabetes

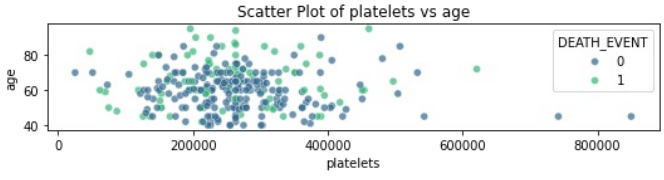

Scatter Plot of diabetes vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0.0
0.2
0.4
0.6
0.8
1.0
diabetes

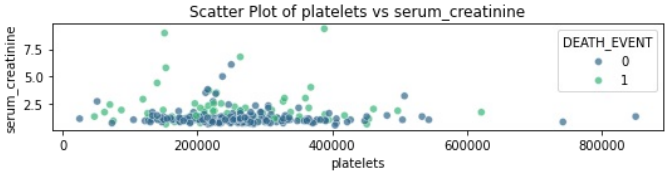

Scatter Plot of ejection_fraction vs age
DEATH_EVENT
0
1
age
40
60
80
20
30
40
50
60
70
80
ejection_fraction

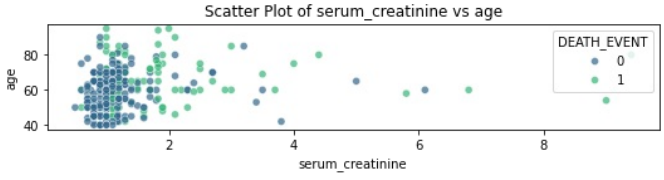

Scatter Plot of ejection_fraction vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
20
30
40
50
60
70
80
ejection_fraction

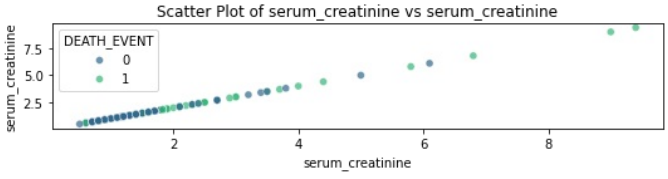

Scatter Plot of high_blood_pressure vs age
DEATH_EVENT
0
1
age
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
high_blood_pressure

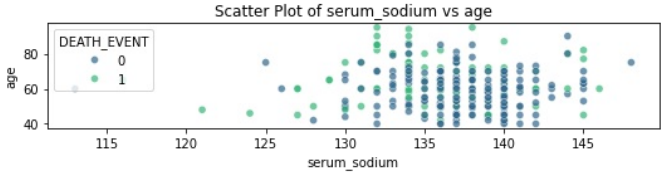

Scatter Plot of high_blood_pressure vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0.0
0.2
0.4
0.6
0.8
1.0
high_blood_pressure

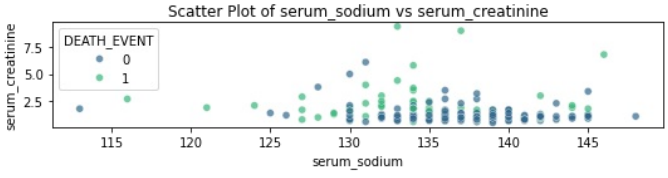

Scatter Plot of platelets vs age
DEATH_EVENT
0
1
age
40
60
80
0
200000
400000
600000
800000
platelets


Scatter Plot of platelets vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0
200000
400000
600000
800000
platelets


Scatter Plot of serum_creatinine vs age
DEATH_EVENT
0
1
age
40
60
80
2
4
6
8
serum_creatinine


Scatter Plot of serum_creatinine vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
2
4
6
8
serum_creatinine


Scatter Plot of serum_sodium vs age
DEATH_EVENT
0
1
age
40
60
80
115
120
125
130
135
140
145
serum_sodium

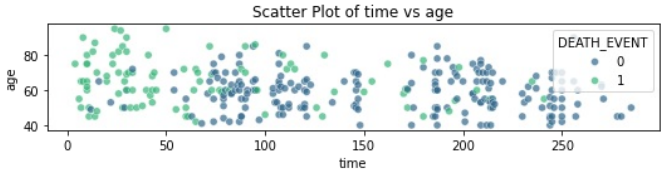

Scatter Plot of serum_sodium vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
115
120
125
130
135
140
145
serum_sodium

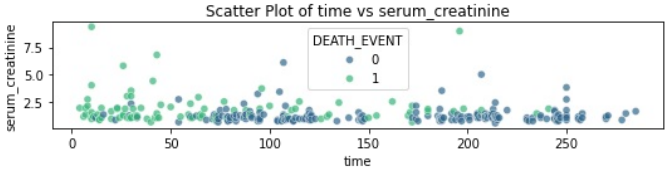

Scatter Plot of sex vs age
DEATH_EVENT
0
1
age
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
sex


Scatter Plot of sex vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0.0
0.2
0.4
0.6
0.8
1.0
sex


Scatter Plot of smoking vs age
DEATH_EVENT
0
1
age
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
smoking


Scatter Plot of smoking vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0.0
0.2
0.4
0.6
0.8
1.0
smoking


Scatter Plot of time vs age
DEATH_EVENT
0
1
age
40
60
80
0
50
100
150
200
250
time


Scatter Plot of time vs serum_creatinine
DEATH_EVENT
0
1
serum_creatinine
2.5
5.0
7.5
0
50
100
150
200
250
time

Support vector machine (SVM)

In [ ]:

```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC

# Select features
selected_features = ['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes', 'ejection_fraction',
 'high_blood_pressure', 'platelets', 'serum_creatinine', 'serum_sodium', 'sex', 'smoking', 'time']

# Prepare the data for SVM
X = data_df[selected_features]
y = data_df['DEATH_EVENT']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create an SVM model
model = SVC()

# Train the model
model.fit(X_train, y_train)

# Evaluate the model
accuracy = model.score(X_test, y_test)
print(f"SVM Accuracy: {accuracy:.2f}")

# Randomly sample rows from the DataFrame
random_sample = data_df[selected_features].sample(n=1, random_state=42)

# Make a prediction
y_pred = model.predict(random_sample)
print("Predicted DEATH_EVENT:", y_pred[0])
```

```
SVM Accuracy: 0.58
Predicted DEATH_EVENT: 0
```

Logistic Regression

In [ ]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Load the dataset
data_df = pd.read_csv('heart_failure_clinical_records_dataset.csv')

# Select features for the scatter plot
selected_features = ['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes', 'ejection_fraction',
 'high_blood_pressure', 'platelets', 'serum_creatinine', 'serum_sodium', 'sex', 'smoking', 'time']

# Prepare the data for Logistic Regression
X = data_df[selected_features]
y = data_df['DEATH_EVENT']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state=42)

# Create a Logistic Regression model
logistic_model = LogisticRegression()

# Train the model
logistic_model.fit(X_train, y_train)

# Evaluate the model
y_pred_logistic = logistic_model.predict(X_test)

# Calculate accuracy
accuracy_logistic = accuracy_score(y_test, y_pred_logistic)
print(f"Logistic Regression Accuracy: {accuracy_logistic:.2f}")

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred_logistic)
print("Confusion Matrix:")
print(conf_matrix)

# Classification Report
classification_rep = classification_report(y_test, y_pred_logistic)
print("\nClassification Report:")
print(classification_rep)

# Randomly sample rows from the DataFrame
random_sample = data_df[selected_features].sample(n=1,random_state=42)

# Make a prediction using Logistic Regression
pred_logistic_sample = logistic_model.predict(random_sample)
```

```
print("\nLogistic Regression Predicted DEATH_EVENT:", pred_logistic_sample[0])
```

```
Logistic Regression Accuracy: 0.80
Confusion Matrix:
[[33  2]
 [10 15]]

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.94      0.85        35
           1       0.88      0.60      0.71        25

    accuracy                           0.80        60
   macro avg       0.82      0.77      0.78        60
weighted avg       0.82      0.80      0.79        60


Logistic Regression Predicted DEATH_EVENT: 0
```

DecisionTreeClassifier

In [ ]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

# Load the dataset
data_df = pd.read_csv('heart_failure_clinical_records_dataset.csv')
data_df.head()

# Select features for the scatter plot
selected_features = ['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes', 'ejection_fraction',
 'high_blood_pressure', 'platelets', 'serum_creatinine','serum_sodium', 'sex', 'smoking', 'time']


# Prepare the data for decision tree
X = data_df[selected_features]
y = data_df['DEATH_EVENT']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a Decision Tree model
model = DecisionTreeClassifier()

# Train the model
model.fit(X_train, y_train)

# Evaluate the model
accuracy = model.score(X_test, y_test)
print(f"Decision tree Accuracy: {accuracy:.2f}")

# Randomly sample rows from the DataFrame
random_sample = data_df[selected_features].sample(n=1,random_state=42)

# Make a prediction
y_pred = model.predict(random_sample)
print("Predicted DEATH_EVENT:", y_pred[0])
```

```
Decision tree Accuracy: 0.65
Predicted DEATH_EVENT: 1
```

RandomForestClassifier

In [ ]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier  # Import RandomForestClassifier


# Select features for the scatter plot
selected_features = ['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes', 'ejection_fraction',
 'high_blood_pressure', 'platelets', 'serum_creatinine','serum_sodium', 'sex', 'smoking', 'time']

# Prepare the data for Random Forest
X = data_df[selected_features]
y = data_df['DEATH_EVENT']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a Random Forest model
model = RandomForestClassifier(random_state=42)  # Use RandomForestClassifier

# Train the model
```

```
model.fit(X_train, y_train)

# Evaluate the model
accuracy = model.score(X_test, y_test)
print(f"RandomForestClassifier Accuracy: {accuracy:.2f}")

# Randomly sample rows from the DataFrame
random_sample = data_df[selected_features].sample(n=1, random_state=42)

# Make a prediction
y_pred = model.predict(random_sample)
print("Predicted DEATH_EVENT:", y_pred[0])
```

```
RandomForestClassifier Accuracy: 0.75
Predicted DEATH_EVENT: 0
```

KNeighborsClassifier

In [ ]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier  # Import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler

# Select features for the scatter plot
selected_features = ['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes', 'ejection_fraction',
 'high_blood_pressure', 'platelets', 'serum_creatinine','serum_sodium', 'sex', 'smoking', 'time']

# Prepare the data for K-Nearest Neighbors
X = data_df[selected_features]
y = data_df['DEATH_EVENT']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a K-Nearest Neighbors model
k = 5  # You can choose the value of k based on your requirements
model = KNeighborsClassifier(n_neighbors=k)  # Use KNeighborsClassifier instead of RandomForestClassifier

# Train the model
model.fit(X_train, y_train)

# Evaluate the model
accuracy = model.score(X_test, y_test)
print(f"K-Nearest Neighbors model Accuracy: {accuracy:.2f}")

# Randomly sample rows from the DataFrame
random_sample = data_df[selected_features].sample(n=1, random_state=42)

# Make a prediction
y_pred = model.predict(random_sample)
print("Predicted DEATH_EVENT:", y_pred[0])
```

```
K-Nearest Neighbors model Accuracy: 0.53
Predicted DEATH_EVENT: 1
```

General Conclusions

In the context of heart failure prediction from the same dataset, Logistic Regression emerges as the top performer with an accuracy of 80%, demonstrating its effectiveness. Random Forest Classifier follows closely with 75% accuracy, displaying robustness in handling complex relationships. Decision Tree performs moderately at 65%. Support Vector Machines (SVM) achieved 58%, showing potential sensitivity to the data's linear separability. K-Nearest Neighbors (KNN) trails with 53%, suggesting the need for parameter adjustments. While Logistic Regression and Random Forest excel, further exploration and parameter tuning could enhance the performance of SVM, Decision Tree, and KNN in this specific prediction task.