Email Classification and Prediction using Machine Learning

Submitted By: -

Steps to be followed:

- 1. Data loading and understanding
- 2. Data Cleaning
- 3. Data preprocessing
- 4. Data Visualization (EDA)
- 5. Feature extraction
- 6. Topic modelling
- 7. Model building
- 8. Model Evaluation
- 9. Prediction of Emails

In [1]:

```
# Importing necessary Libraries
import pandas as pd
import numpy as np
# Importing NLTK Library for Text processing
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.tokenize import RegexpTokenizer
from collections import Counter
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt
# Libraries for Visualisation
import plotly.graph objects as go
from sklearn.model selection import train test split
# For conversion of text
from sklearn.feature_extraction.text import TfidfVectorizer
# Machine Learning Models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
# Metrics
from sklearn.metrics import accuracy score
from sklearn.metrics import classification_report
```

In [2]:

```
# Importing the data
data = pd.read_csv(r"C:\Users\Tanmayee\OneDrive\Documents\Personal\Other\Coventry\Bhanu\mail_data.csv
data
```

Out[2]:

| | Category | Message |
|------|----------|--|
| 0 | ham | Go until jurong point, crazy Available only |
| 1 | ham | Ok lar Joking wif u oni |
| 2 | spam | Free entry in 2 a wkly comp to win FA Cup fina |
| 3 | ham | U dun say so early hor U c already then say |
| 4 | ham | Nah I don't think he goes to usf, he lives aro |
| | | |
| 5567 | spam | This is the 2nd time we have tried 2 contact u |
| 5568 | ham | Will ü b going to esplanade fr home? |
| 5569 | ham | Pity, * was in mood for that. Soany other s |
| 5570 | ham | The guy did some bitching but I acted like i'd |
| 5571 | ham | Rofl. Its true to its name |

5572 rows × 2 columns

In [3]:

```
# Finding out number of rows and columns in dataset data.shape
```

Out[3]:

(5572, 2)

In [4]:

```
# Type of data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 2 columns):
    # Column Non-Null Count Dtype
--- 0 Category 5572 non-null object
    1 Message 5572 non-null object
dtypes: object(2)
memory usage: 87.2+ KB
```

In [5]:

```
data.describe()
```

Out[5]:

| | Category | Message |
|--------|----------|------------------------|
| count | 5572 | 5572 |
| unique | 2 | 5157 |
| top | ham | Sorry, I'll call later |
| freq | 4825 | 30 |

In [6]:

```
# Check for null values in the DataFrame
null_values = data.isnull().sum()

# Display the columns with null values
print("Columns with null values:")
print(null_values[null_values > 0])
```

Columns with null values:
Series([], dtype: int64)

In [7]:

```
# Replace null values with an empty string
df = data.fillna('')
```

In [8]:

```
# Create a dictionary to map values
mapping = {'spam': 0, 'ham': 1}

# Update 'Category' values using the mapping dictionary
df['Category'] = df['Category'].map(mapping)

# Display the updated DataFrame
df
```

Out[8]:

| | Category | Message |
|------|----------|--|
| 0 | 1 | Go until jurong point, crazy Available only |
| 1 | 1 | Ok lar Joking wif u oni |
| 2 | 0 | Free entry in 2 a wkly comp to win FA Cup fina |
| 3 | 1 | U dun say so early hor U c already then say |
| 4 | 1 | Nah I don't think he goes to usf, he lives aro |
| | | |
| 5567 | 0 | This is the 2nd time we have tried 2 contact u |
| 5568 | 1 | Will ü b going to esplanade fr home? |
| 5569 | 1 | Pity, * was in mood for that. Soany other s |
| 5570 | 1 | The guy did some bitching but I acted like i'd |
| 5571 | 1 | Rofl. Its true to its name |

In [9]:

```
import plotly.express as px

# Assuming 'data' is your DataFrame containing the 'Category' column
fig = px.histogram(data, x='Category')

# Display the plot
fig.show()
```



In [10]:

```
# Function to clean the text
def clean_text(text):
    # Remove special characters and numbers
    text = re.sub('[^a-zA-Z]', ' ', text)

# Convert text to Lowercase
    text = text.lower()

# Tokenize the text
    tokens = word_tokenize(text)

# Remove stopwords
    stop_words = set(stopwords.words('english'))
    filtered_tokens = [token for token in tokens if token not in stop_words]

# Join the tokens back into a single string
    cleaned_text = ' '.join(filtered_tokens)

return cleaned_text
```

```
In [11]:
# Apply the cleaning function to the "Message" column
df['Message'] = df['Message'].apply(clean_text)
In [12]:
df['Message']
Out[12]:
0
        go jurong point crazy available bugis n great ...
                                  ok lar joking wif u oni
1
        free entry wkly comp win fa cup final tkts st ...
2
3
                      u dun say early hor u c already say
4
                   nah think goes usf lives around though
        nd time tried contact u u pound prize claim ea...
5567
                                b going esplanade fr home
5568
5569
                                    pity mood suggestions
5570
        guy bitching acted like interested buying some...
5571
                                           rofl true name
Name: Message, Length: 5572, dtype: object
In [13]:
import vaderSentiment
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
ana = SentimentIntensityAnalyzer()
In [14]:
def sa_score(sentence):
   marks = ana.polarity_scores(sentence)
    print(f"{sentence:-<40} {str(marks)}")</pre>
In [15]:
#testing the function
m1 = "b going esplanade fr home"
m2 = "pity mood suggestions"
m3 = "I am not able to classify the emails in respective folders"
print (sa score(m1))
print (sa_score(m2))
print (sa_score(m3))
b going esplanade fr home------ {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compoun
d': 0.0}
None
pity mood suggestions----- { 'neg': 0.524, 'neu': 0.476, 'pos': 0.0, 'comp
ound': -0.296}
None
I am not able to classify the emails in respective folders {'neg': 0.0, 'neu': 0.781,
'pos': 0.219, 'compound': 0.4215}
```

None

In [16]:

tokenizer = RegexpTokenizer(r'\w+')

```
In [17]:
```

Print the results

```
wd = df['Message'].apply(tokenizer.tokenize)
wd.head()
Out[17]:
     [go, jurong, point, crazy, available, bugis, n...
1
                        [ok, lar, joking, wif, u, oni]
     [free, entry, wkly, comp, win, fa, cup, final,...
3
         [u, dun, say, early, hor, u, c, already, say]
4
        [nah, think, goes, usf, lives, around, though]
Name: Message, dtype: object
In [18]:
# Flatten the list of word tokens
complete = [word for tokens in wd for word in tokens]
# Calculate the lengths of each word token list
dl = [len(tokens) for tokens in wd]
# Create a vocabulary set from all the word tokens
VOCAB = sorted(list(set(word for tokens in wd for word in tokens)))
```

50385 words total, with a vocabulary size of 7637

print(f"{len(complete)} words total, with a vocabulary size of {len(VOCAB)}")

In [19]:

```
# Checking most common words
count_complete = Counter(complete)
count_complete.most_common(100)
```

Out[19]:

```
[('u', 1224),
 ('call', 605),
 ('get', 397),
 ('ur', 391),
 ('gt', 318),
 ('Īt', 316),
 ('ok', 293),
 ('go', 289),
 ('free', 288),
 ('know', 262),
 ('got', 253),
 ('like', 247),
 ('good', 247),
 ('day', 244),
 ('come', 233),
('time', 221),
('love', 215),
('send', 200),
('want', 196),
 ('text', 195),
 ('p', 188),
 ('txt', 184),
 ('n', 176),
 ('one', 176),
 ('going', 173),
 ('r', 171),
 ('need', 169),
 ('home', 167),
 ('stop', 163),
 ('lor', 162),
 ('k', 160),
 ('today', 160),
 ('sorry', 160),
 ('see', 159),
 ('still', 158),
 ('back', 153),
 ('da', 151),
 ('dont', 149),
 ('reply', 148),
('mobile', 144),
 ('take', 140),
 ('hi', 140),
 ('tell', 139),
 ('new', 136),
 ('please', 135),
('later', 135),
 ('pls', 134),
 ('think', 132),
 ('c', 127),
 ('phone', 127),
 ('dear', 125),
 ('week', 124),
 ('well', 120),
 ('night', 118),
 ('much', 116),
 ('great', 115),
 ('oh', 115),
 ('hope', 114),
 ('msg', 113),
 ('hey', 112),
 ('claim', 111),
 ('na', 109),
 ('happy', 108),
('wat', 107),
 ('b', 107),
 ('give', 104),
 ('yes', 103),
```

```
('way', 103),

| **(way', 102),
| **(way
```

email body_{text}

In [21]:

```
# Apply sentiment analysis to each review in 'body_new' column
df['scores'] = df['Message'].map(lambda review: ana.polarity_scores(review))

# Extract the compound score from the 'scores' dictionary
df['compound'] = df['scores'].map(lambda score_dict: score_dict['compound'])

# Assign sentiment labels based on the compound score
df['Sentiment'] = df['compound'].map(lambda x: 'Positive' if x >= 0.05 else 'Negative' if x <= -0.05</pre>
```

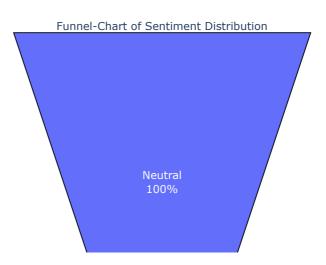
The error is solved using below code.

In [22]:

```
# Grouping and aggregating the data
var1 = df['Message'].groupby(df['Sentiment']).count().reset_index().sort_values(by='Message', ascending
# Creating the figure object
fig = go.Figure()

# Adding the Funnel area trace
fig.add_trace(
    go.Funnelarea(
        text=var1['Sentiment'],
        values=var1['Message'],
        title="Funnel-Chart of Sentiment Distribution",
        textposition="inside",
        marker=dict(colors=["#636EFA", "#EF553B", "#00CC96"], line=dict(color='#000000', width=1))
)

# Displaying the figure
fig.show()
```



```
In [23]:
```

```
stopwords = set(STOPWORDS)
df_positive = df[df["Sentiment"] == "Positive"]
comment_words = ' '.join(df_positive.Message.astype(str).str.lower())
# Concatenate all positive messages into a single string
comment_words = ' '.join(df_positive.Message.astype(str).str.lower())
# Check if there are words to generate the word cloud
if len(comment_words) > 0:
    # Create the WordCloud object
    wordcloud = WordCloud(width=800, height=800, background_color='white', stopwords=stopwords)
    # Generate the word cloud
   wordcloud.generate(comment_words)
   # Plot the word cloud
    plt.figure(figsize=(8, 8))
    plt.imshow(wordcloud)
    plt.axis('off')
    plt.show()
else:
    print("No words found to generate the word cloud.")
```

No words found to generate the word cloud.

In [24]:

```
# Create a dictionary to map values
mapping = {'spam': 0, 'ham': 1}

# Update 'Category' values using the mapping dictionary
data['Category'] = data['Category'].map(mapping)
```

In [25]:

```
Texts = data['Message']
Label = data['Category']
```

In [26]:

```
# Split the data into a training set (70%) and a test set (30%)
X_train, X_test, y_train, y_test = train_test_split(Texts, Label, test_size=0.3, random_state=42)
# Print the shape of the training and test sets
print("Train Data:", X_train.shape, y_train.shape)
print("Test Data:", X_test.shape, y_test.shape)
```

Train Data: (3900,) (3900,) Test Data: (1672,) (1672,)

```
In [27]:
# Feature Extraction
# Transforming Text Data to feature vector that is used as input to Machine Learning Models.
# Create an instance of TfidfVectorizer
feature_extraction = TfidfVectorizer(min_df=1, stop_words='english', lowercase=True)
# Fit and transform the training set
X_train_features = feature_extraction.fit_transform(X_train)
# Transform the test set
X_test_features = feature_extraction.transform(X_test)
In [28]:
# Convert Y train and Y test as integer
y_train = y_train.astype('int')
y_test = y_test.astype('int')
Logistic Regression
In [29]:
model = LogisticRegression()
In [30]:
model.fit(X_train_features,y_train)
Out[30]:
LogisticRegression()
In [31]:
pred_LR_train = model.predict(X_train_features)
accuracy_LR_train = accuracy_score(y_train,pred_LR_train)
accuracy_LR_train
Out[31]:
0.963076923076923
In [32]:
pred_LR_test = model.predict(X_test_features)
accuracy_LR_test = accuracy_score(y_test,pred_LR_test)
accuracy_LR_test
Out[32]:
```

0.9659090909090909

```
In [33]:
```

```
# Generate the classification report
classification_report_LR = classification_report(y_test, pred_LR_test)
# Print the classification report
print(classification_report_LR)
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.99 | 0.75 | 0.86 | 224 |
| 1 | 0.96 | 1.00 | 0.98 | 1448 |
| accuracy | | | 0.97 | 1672 |
| macro avg | 0.98 | 0.88 | 0.92 | 1672 |
| weighted avg | 0.97 | 0.97 | 0.96 | 1672 |

Hyper parameter Tunning

In [34]:

```
from sklearn.preprocessing import MaxAbsScaler

# Scale the features using MaxAbsScaler
scaler = MaxAbsScaler()
X_train_features_scaled = scaler.fit_transform(X_train_features)
X_test_features_scaled = scaler.transform(X_test_features)

# Create the Logistic Regression model and fit with scaled features
model = LogisticRegression(max_iter=1000)
model.fit(X_train_features_scaled, y_train)
```

Out[34]:

LogisticRegression(max_iter=1000)

In [35]:

```
# Create the Logistic Regression model with the 'saga' solver
model = LogisticRegression(max_iter=1000, solver='saga')
model.fit(X_train_features, y_train)
```

Out[35]:

LogisticRegression(max_iter=1000, solver='saga')

In [36]:

```
# Create the Logistic Regression model with L2 regularization (Ridge)
model = LogisticRegression(max_iter=1000, penalty='12')
model.fit(X_train_features, y_train)
```

Out[36]:

LogisticRegression(max_iter=1000)

```
In [37]:
from sklearn.metrics import accuracy_score
# Train accuracy for the model with max_iter=1000
pred_train = model.predict(X_train_features_scaled)
accuracy_train = accuracy_score(y_train, pred_train)
print("Train Accuracy (max_iter=1000):", accuracy_train)
# Test accuracy for the model with max iter=1000
pred_test = model.predict(X_test_features_scaled)
accuracy_test = accuracy_score(y_test, pred_test)
print("Test Accuracy (max_iter=1000):", accuracy_test)
# Train accuracy for the model with 'saga' solver
pred_train_saga = model.predict(X_train_features)
accuracy_train_saga = accuracy_score(y_train, pred_train_saga)
print("Train Accuracy (solver='saga'):", accuracy_train_saga)
# Test accuracy for the model with 'saga' solver
pred test saga = model.predict(X test features)
accuracy_test_saga = accuracy_score(y_test, pred_test_saga)
print("Test Accuracy (solver='saga'):", accuracy_test_saga)
# Train accuracy for the model with L2 regularization (Ridge)
pred_train_ridge = model.predict(X_train_features)
accuracy_train_ridge = accuracy_score(y_train, pred_train_ridge)
print("Train Accuracy (L2 regularization - Ridge):", accuracy_train_ridge)
# Test accuracy for the model with L2 regularization (Ridge)
pred_test_ridge = model.predict(X_test_features)
accuracy_test_ridge = accuracy_score(y_test, pred_test_ridge)
print("Test Accuracy (L2 regularization - Ridge):", accuracy_test_ridge)
Train Accuracy (max iter=1000): 0.99
Test Accuracy (max_iter=1000): 0.9850478468899522
Train Accuracy (solver='saga'): 0.963076923076923
Test Accuracy (solver='saga'): 0.9659090909090909
Train Accuracy (L2 regularization - Ridge): 0.963076923076923
Test Accuracy (L2 regularization - Ridge): 0.965909090909090909
Random Forest
In [38]:
```

```
# Create a Random Forest classifier object
rf_classifier = RandomForestClassifier()

# Fit the classifier on the training data
rf_classifier.fit(X_train_features, y_train)
```

```
Out[38]:
```

RandomForestClassifier()

```
In [39]:
```

```
pred_RF_train =rf_classifier.predict(X_train_features)
accuracy_RF_train = accuracy_score(y_train,pred_RF_train)
accuracy_RF_train
```

```
Out[39]:
```

```
In [40]:
```

```
pred_RF_test = rf_classifier.predict(X_test_features)
accuracy_RF_test = accuracy_score(y_test,pred_RF_test)
accuracy_RF_test
```

Out[40]:

0.9796650717703349

In [41]:

```
# Generate the classification report
classification_report_RF = classification_report(y_test, pred_RF_test)
# Print the classification report
print(classification_report_RF)
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| | | | | |
| 0 | 1.00 | 0.85 | 0.92 | 224 |
| 1 | 0.98 | 1.00 | 0.99 | 1448 |
| | | | | |
| accuracy | | | 0.98 | 1672 |
| macro avg | 0.99 | 0.92 | 0.95 | 1672 |
| weighted avg | 0.98 | 0.98 | 0.98 | 1672 |

Hyper parameter Tunning Random Forest

In [42]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
# Create the Random Forest classifier
rf_classifier = RandomForestClassifier()
# Define the hyperparameters to search
param_grid = {
    'n_estimators': [50, 100, 150], # Number of trees in the forest
    'max_depth': [None, 10, 20, 30], # Maximum depth of the trees
    'min_samples_split': [2, 5, 10], # Minimum number of samples required to split an internal node
    'min_samples_leaf': [1, 2, 4]
                                    # Minimum number of samples required to be at a leaf node
}
# Create the Grid Search object
grid_search = GridSearchCV(rf_classifier, param_grid, cv=5, scoring='accuracy')
# Perform Grid Search with training data
grid_search.fit(X_train_features, y_train)
# Get the best hyperparameters and corresponding accuracy
best params = grid search.best params
best_accuracy = grid_search.best_score_
print("Best Hyperparameters:", best_params)
print("Best Accuracy:", best_accuracy)
```

```
Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 1
0, 'n_estimators': 100}
Best Accuracy: 0.9753846153846153
```

Decision Tree

```
In [43]:
```

```
# Create a Decision Tree classifier object
dt_classifier = DecisionTreeClassifier()

# Fit the classifier on the training data
dt_classifier.fit(X_train_features, y_train)
```

Out[43]:

DecisionTreeClassifier()

In [44]:

```
pred_DT_train =dt_classifier.predict(X_train_features)
accuracy_DT_train = accuracy_score(y_train,pred_DT_train)
accuracy_DT_train
```

Out[44]:

1.0

In [45]:

```
pred_DT_test = dt_classifier.predict(X_test_features)
accuracy_DT_test = accuracy_score(y_test,pred_DT_test)
accuracy_DT_test
```

Out[45]:

0.9700956937799043

In [46]:

```
# Generate the classification report
classification_report_DT = classification_report(y_test, pred_DT_test)
# Print the classification report
print(classification_report_DT)
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.92 | 0.85 | 0.88 | 224 |
| 1 | 0.98 | 0.99 | 0.98 | 1448 |
| accuracy | | | 0.97 | 1672 |
| macro avg | 0.95 | 0.92 | 0.93 | 1672 |
| weighted avg | 0.97 | 0.97 | 0.97 | 1672 |

Hyper parameter Tunning

```
In [47]:
from sklearn.tree import DecisionTreeClassifier
from sklearn.model selection import GridSearchCV
# Create the Decision Tree classifier
dt classifier = DecisionTreeClassifier()
# Define the hyperparameters to search
param_grid = {
    'criterion': ['gini', 'entropy'], # Criteria for choosing attributes
    'max_depth': [None, 10, 20, 30], # Maximum depth of the tree
    'min_samples_split': [2, 5, 10], # Minimum number of samples required to split an internal node
    'min_samples_leaf': [1, 2, 4]
                                       # Minimum number of samples required to be at a leaf node
}
# Create the Grid Search object
grid_search = GridSearchCV(dt_classifier, param_grid, cv=5, scoring='accuracy')
# Perform Grid Search with training data
grid_search.fit(X_train_features, y_train)
# Get the best hyperparameters and corresponding accuracy
best_params = grid_search.best_params_
best_accuracy = grid_search.best_score_
print("Best Hyperparameters:", best_params)
print("Best Accuracy:", best_accuracy)
Best Hyperparameters: {'criterion': 'gini', 'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 5}
Best Accuracy: 0.9592307692307692
SVM
In [48]:
# Create an SVM classifier object
svm_classifier = SVC()
# Fit the classifier on the training data
svm classifier.fit(X train features, y train)
Out[48]:
SVC()
```

```
In [49]:
```

```
pred_SVM_train =svm_classifier.predict(X_train_features)
accuracy_SVM_train = accuracy_score(y_train,pred_SVM_train)
accuracy_SVM_train
```

```
Out[49]:
```

0.9987179487179487

In [50]:

```
pred_SVM_test = svm_classifier.predict(X_test_features)
accuracy_SVM_test = accuracy_score(y_test,pred_SVM_test)
accuracy_SVM_test
```

Out[50]:

0.9832535885167464

In [51]:

```
# Generate the classification report
classification_report_SVM = classification_report(y_test, pred_SVM_test)
# Print the classification report
print(classification_report_SVM)
```

| | precision | recall | f1-score | support |
|---------------------------------------|--------------|--------------|----------------------|----------------------|
| 0 1 | 1.00 0.98 | 0.88 1.00 | 0.93 0.99 | 224 1448 |
| accuracy macro avg weighted avg | 0.99 0.98 | 0.94 0.98 | 0.98 0.96 0.98 | 1672 1672 1672 |

Comparison of Classification Report

In [52]:

```
# Create a list of model names
models = ['Logistic Regression', 'Random Forest', 'Decision Tree', 'SVM']

# Create a list of predicted labels
preds = [pred_LR_test, pred_RF_test, pred_DT_test, pred_SVM_test]

# Create an empty list to store the classification reports
classification_reports = []

# Generate the classification reports for each model and store them
for model_name, pred in zip(models, preds):
    report = classification_report(y_test, pred)
    classification_reports.append((model_name, report))

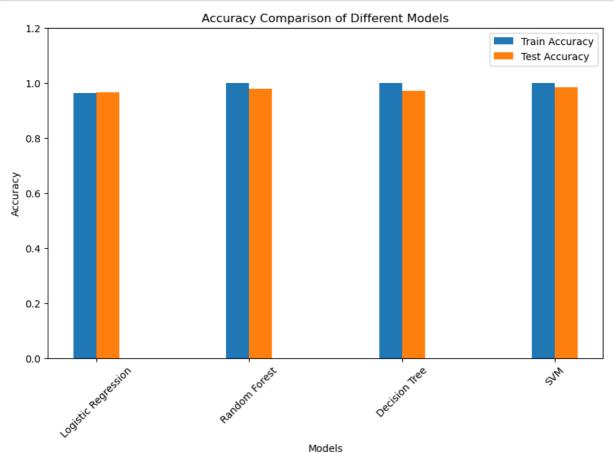
# Print the classification reports side by side
for model_name, report in classification_reports:
    print(f"Classification Report for {model_name}:")
    print(report)
    print("\n" + "=" * 80 + "\n")
```

| Classificatio | n Report for precision | | | n: support | |
|---|---|---|---|---|---|
| 0 | 0.99 | 0.75 | 0.86 | 224 | |
| 1 | 0.96 | 1.00 | 0.98 | 1448 | |
| | | | | | |
| accuracy | | | 0.97 | 1672 | |
| macro avg | | | 0.92 | 1672 | |
| weighted avg | 0.97 | 0.97 | 0.96 | 1672 | |
| | .======== | | ======== | | |
| Classificatio | | | | | |
| | precision | | | support | |
| | | | | | |
| 0 | 1.00 | 0.85 | 0.92 | 224 | |
| 1 | 0.98 | 1.00 | 0.99 | 1448 | |
| accuracy | | | 0.98 | 1672 | |
| macro avg | 0.99 | 0.92 | | | |
| weighted avg | 0.98 | 0.98 | 0.98 | 1672 | |
| | | | | | |
| Classificatio | | Decision | Tree: | support | ======================================= |
| | n Report for | Decision recall | Tree: f1-score | | ======================================= |
| Classificatio | n Report for precision | Decision recall | Tree: f1-score | support | ======================================= |
| Classificatio 0 1 | n Report for precision 0.92 | Decision recall | Tree: f1-score 0.88 0.98 | support 224 1448 | ======================================= |
| Classificatio 0 1 accuracy | on Report for precision 0.92 0.98 | Decision recall 0.85 0.99 | Tree: f1-score 0.88 0.98 0.97 | support 224 1448 1672 | ======================================= |
| Classificatio 0 1 accuracy macro avg | on Report for precision 0.92 0.98 | Decision recall 0.85 0.99 | Tree: f1-score 0.88 0.98 0.97 0.93 | support 224 1448 1672 1672 | ======================================= |
| Classificatio 0 1 accuracy macro avg | on Report for precision 0.92 0.98 | Decision recall 0.85 0.99 | Tree: f1-score 0.88 0.98 0.97 | support 224 1448 1672 | ======================================= |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 support | |
| Classificatio 0 1 accuracy macro avg weighted avg =================================== | n Report for precision 0.92 0.98 0.95 0.97 n Report for precision 1.00 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 support | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 support | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 n Report for precision 1.00 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 support | |
| Classificatio 0 1 accuracy macro avg weighted avg Classificatio 0 1 accuracy macro avg | n Report for precision 0.92 0.98 0.95 0.97 n Report for precision 1.00 0.98 | Decision recall 0.85 0.99 0.92 0.97 SVM: recall 0.88 1.00 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 | support 224 1448 1672 1672 1672 support 224 1448 1672 1672 | |
| Classificatio 0 1 accuracy macro avg weighted avg | n Report for precision 0.92 0.98 0.95 0.97 n Report for precision 1.00 0.98 | Decision recall 0.85 0.99 0.92 0.97 | Tree: f1-score 0.88 0.98 0.97 0.93 0.97 f1-score 0.93 0.99 0.98 | support 224 1448 1672 1672 1672 support 224 1448 1672 | |

Comparison of Accuracy

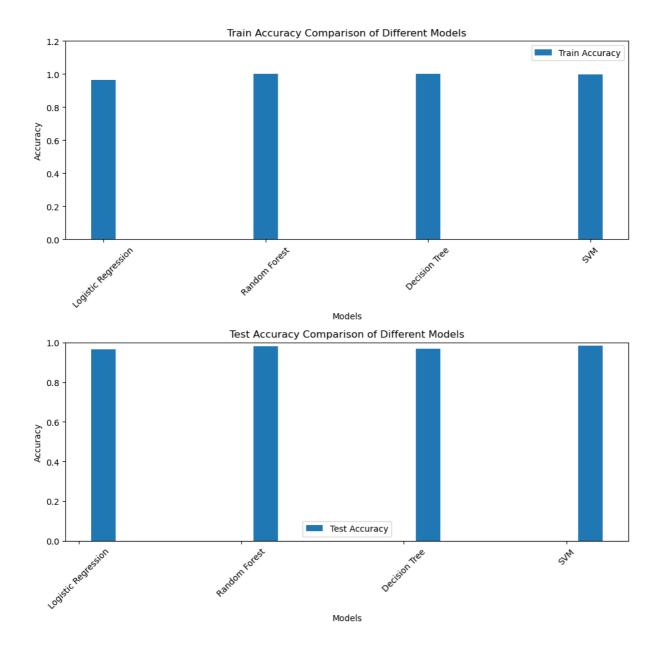
In [53]:

```
# Accuracy values
accuracies_train = [accuracy_LR_train, accuracy_RF_train, accuracy_DT_train, accuracy_SVM_train]
accuracies_test = [accuracy_LR_test, accuracy_RF_test, accuracy_DT_test, accuracy_SVM_test]
# Model names
models = ['Logistic Regression', 'Random Forest', 'Decision Tree', 'SVM']
# Set the width of the bars
bar_width = 0.15
# Define the positions of the bars
train_positions = np.arange(len(models))
test_positions = train_positions + bar_width
# Plotting the accuracy graphs
plt.figure(figsize=(10, 6))
plt.bar(train_positions, accuracies_train, label='Train Accuracy', width=bar_width)
plt.bar(test_positions, accuracies_test, label='Test Accuracy', width=bar_width)
plt.ylim(0, 1.2)
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Accuracy Comparison of Different Models')
plt.legend()
plt.xticks(train_positions + bar_width / 2, models, rotation=45)
plt.show()
```



In [54]:

```
# Create subplots
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(10, 10))
# Plotting the train accuracy graph
ax1.bar(train_positions, accuracies_train, label='Train Accuracy', width=bar_width)
ax1.set_ylim(0, 1.2)
ax1.set_xlabel('Models')
ax1.set_ylabel('Accuracy')
ax1.set_title('Train Accuracy Comparison of Different Models')
ax1.set_xticks(train_positions)
ax1.set_xticklabels(models, rotation=45)
ax1.legend()
# Plotting the test accuracy graph
ax2.bar(test_positions, accuracies_test, label='Test Accuracy', width=bar_width)
ax2.set_ylim(0, 1.)
ax2.set_xlabel('Models')
ax2.set_ylabel('Accuracy')
ax2.set_title('Test Accuracy Comparison of Different Models')
ax2.set_xticks(train_positions)
ax2.set_xticklabels(models, rotation=45)
ax2.legend()
# Adjust spacing between subplots
plt.tight_layout()
# Show the plots
plt.show()
```



As seen from the above results both Random Forest and SVM has performed well in terms of Accuracy. So we will select the SVM model to classify the emails

Building Prediction Model

```
In [55]:
```

```
data_input = ["SIX chances to win CASH! From 100 to 20,000 pounds txt> CSH11 and send to 87575. Cost :
# Convert text to numbers
ndata = feature_extraction.transform(data_input)
```

In [56]:

```
# Making Predictions for the new email 'ndata'
prediction = svm_classifier.predict(ndata)

if prediction[0] == 1:
    print('It is a ham mail')
else:
    print('It is a spam mail')
```

It is a spam mail