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Final Project Report

Implementation and Code Usage

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3 Algorithm Implementation on Transaction Dataset

Abstract:
This project focuses on exploring and comparing machine learning models for product recommendation based on customer purchase history. The project involves data preprocessing, including handling missing values and encoding categorical variables. Three models are developed and evaluated: Random Forest, Naive Bayes, and Convolutional Neural Network (Conv1D). Performance metrics such as True Positive Rate (TPR), Specificity (SPC), Precision (PPV), Accuracy (ACC), and others are used to assess the models' effectiveness. The results are analyzed to determine the best-performing model for product recommendation in a retail setting.

Introduction:
Data mining techniques play a pivotal role in extracting valuable insights and patterns from large datasets. In this project, we explore and evaluate three distinct machine learning models including Random Forest, Naive Bayes, and Convolutional Neural Network for various tasks in a retail setting. The objective is to leverage these models to uncover associations previously unknown.

My primary focus lies in the calculation of the performance metrics that were collected after each of the algorithms ran their classification task. The key steps in this process included:

1. Data Preparation: preparation of the dataset, including features (X) and the target variable (y).
2. Initialization: variables initialized to store True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each fold of cross-validation.
3. Stratified K-Fold Split: employed to ensure that each fold maintains the proportion of classes in the dataset. This method divides the dataset into K folds while preserving the distribution of the target variable across folds.
4. Model Training and Evaluation: for each fold, the model is trained on the training data and evaluated on the testing data.
5. Performance Metric Accumulation: TP, TN, FP, and FN counts are accumulated for each fold to compute aggregate performance metrics across all folds.

Core Algorithms and Principles:

Random Forest:
A random forest is an ensemble learning method that constructs a multitude of decision trees during training. Each tree in the forest is trained on a random subset of the dataset, and their predictions are combined through averaging to enhance predictive accuracy and mitigate overfitting. The trees employ optimal split strategies to improve overall performance, ultimately synthesizing multiple tree outputs into a single result.

Naive Bayes:
Naive Bayes algorithms are a class of supervised learning techniques grounded in Bayes' theorem. They operate under the assumption of conditional independence between features given the class variable, simplifying computation. Despite this simplification, they offer scalability, requiring a parameter count linearly proportional to the number of variables in the problem.

Conv1D:
Convolutional Neural Networks (Conv1D) apply one-dimensional convolution operations to input signals, which consist of multiple input planes. This layer constructs convolution kernels that slide across the input along a single dimension, generating output tensors.

Results and Evaluation:
Based on the metrics given back by each of the algorithms, It is safe to say that the Naive Bayes model works the best to classify a dataset. It was more efficient than both the Random Forest model and the Conv1D model. After much trial and error, it seems that the Conv1D model was the worst of the three and was not a good model to classify the dataset. This can be deduced by looking at the following characteristics:

- Accuracy (ACC): The Naive model has the highest accuracy of 0.83, which means that it correctly predicts 83% of the instances in the dataset.
- True Positive Rate (TPR): The TPR of the Naive model is 0.83, which means it correctly identifies 83% of the positive instances. In contrast, the Conv1D model has a TPR of 0, indicating that it fails to identify any positive instances. This lets us know that the Naive model is better at capturing true positive cases.
- Positive Predictive Value (PPV): The Naive model has a PPV of 0, implying that it does not make any false positive predictions which is a very good statistic. On the other hand, the Conv1D model has a PPV of 0, indicating that all its positive predictions are false. This highlights the much better performance of the Naive model in avoiding false positives.
- Specificity (SPC): The Naive model has a specificity of 1, meaning that it correctly identifies all negative instances. But in contrast, the Conv1D model has a specificity of 0, suggesting that it fails to identify any true negative cases. This further proves the superiority of the Naive model in correctly classifying the dataset.

Screenshots

Here is the csv file (This program takes in 1 csv file to evaluate: ‘invoice_transactions_csv’).

```
Description,Quantity,Price,Customer ID
WHITE HANGING HEART T-LIGHT HOLDER,6,2.55,17850
WHITE METAL LANTERN,6,3.39,17850
CREAM CUPID HEARTS COAT HANGER,8,2.75,17850
KNITTED UNION FLAG HOT WATER BOTTLE,6,3.39,17850
RED WOOLLY HOTTIE WHITE HEART.,6,3.39,17850
SET 7 BABUSHKA NESTING BOXES,2,7.65,17850
GLASS STAR FROSTED T-LIGHT HOLDER,6,4.25,17850
HAND WARMER UNION JACK,6,1.85,17850
HAND WARMER RED POLKA DOT,6,1.85,17850
JAM MAKING SET WITH JARS,6,4.25,13047
RED COAT RACK PARIS FASHION,3,4.95,13047
YELLOW COAT RACK PARIS FASHION,3,4.95,13047
BLUE COAT RACK PARIS FASHION,3,4.95,13047
ASSORTED COLOUR BIRD ORNAMENT,32,1.69,13047
POPPY'S PLAYHOUSE BEDROOM ,6,2.1,13047
POPPY'S PLAYHOUSE KITCHEN,6,2.1,13047
FELTCRAFT PRINCESS CHARLOTTE DOLL,8,3.75,13047
IVORY KNITTED MUG COSY ,6,1.65,13047
BOX OF 6 ASSORTED COLOUR TEASPOONS,6,4.25,13047
BOX OF VINTAGE JIGSAW BLOCKS ,3,4.95,13047
BOX OF VINTAGE ALPHABET BLOCKS,2,9.95,13047
HOME BUILDING BLOCK WORD,3,5.95,13047
LOVE BUILDING BLOCK WORD,3,5.95,13047
RECIPE BOX WITH METAL HEART,4,7.95,13047
DOORMAT NEW ENGLAND,4,7.95,13047
BATH BUILDING BLOCK WORD,3,5.95,13047
ALARM CLOCK BAKELIKE PINK,24,3.75,12583
ALARM CLOCK BAKELIKE RED ,24,3.75,12583
ALARM CLOCK BAKELIKE GREEN,12,3.75,12583
PANDA AND BUNNIES STICKER SHEET,12,0.85,12583
STARS GIFT TAPE ,24,0.65,12583
INFLATABLE POLITICAL GLOBE ,48,0.85,12583
VINTAGE HEADS AND TAILS CARD GAME ,24,1.25,12583
SET/2 RED RETROSPOT TEA TOWELS ,18,2.95,12583
ROUND SNACK BOXES SET OF4 WOODLAND ,24,2.95,12583
SPACEBOY LUNCH BOX ,24,1.95,12583
LUNCH BOX I LOVE LONDON,24,1.95,12583
CIRCUS PARADE LUNCH BOX ,24,1.95,12583
CHARLOTTE BAG DOLLY GIRL DESIGN,20,0.85,12583
RED TOADSTOOL LED NIGHT LIGHT,24,1.65,12583
 SET 2 TEA TOWELS I LOVE LONDON ,24,2.95,12583
VINTAGE SEASIDE JIGSAW PUZZLES,12,3.75,12583
MINI JIGSAW CIRCUS PARADE ,24,0.42,12583
MINI JIGSAW SPACEBOY,24,0.42,12583
MINI PAINT SET VINTAGE ,36,0.65,12583
POSTAGE,3,18,12583
PAPER CHAIN KIT 50'S CHRISTMAS ,80,2.55,13748
HAND WARMER RED POLKA DOT,6,1.85,17850
HAND WARMER UNION JACK,6,1.85,17850
WHITE HANGING HEART T-LIGHT HOLDER,6,2.55,17850
WHITE METAL LANTERN,6,3.39,17850
CREAM CUPID HEARTS COAT HANGER,8,2.75,17850
EDWARDIAN PARASOL RED,6,4.95,17850
RETRO COFFEE MUGS ASSORTED,6,1.06,17850
SAVE THE PLANET MUG,6,1.06,17850
VINTAGE BILLBOARD DRINK ME MUG,6,1.06,17850
VINTAGE BILLBOARD LOVE/HATE MUG,6,1.06,17850
```

```
WOOD 2 DRAWER CABINET WHITE FINISH,2,4.95,17850
WOOD S/3 CABINET ANT WHITE FINISH,4,6.95,17850
WOODEN PICTURE FRAME WHITE FINISH,6,2.1,17850
WOODEN FRAME ANTIQUE WHITE ,6,2.55,17850
KNITTED UNION FLAG HOT WATER BOTTLE,6,3.39,17850
RED WOOLLY HOTTIE WHITE HEART.,6,3.39,17850
SET 7 BABUSHKA NESTING BOXES,2,7.65,17850
GLASS STAR FROSTED T-LIGHT HOLDER,6,4.25,17850
VICTORIAN SEWING BOX LARGE,32,10.95,15100
WHITE HANGING HEART T-LIGHT HOLDER,6,2.55,17850
WHITE METAL LANTERN,6,3.39,17850
CREAM CUPID HEARTS COAT HANGER,8,2.75,17850
EDWARDIAN PARASOL RED,6,4.95,17850
RETRO COFFEE MUGS ASSORTED,6,1.06,17850
SAVE THE PLANET MUG,6,1.06,17850
VINTAGE BILLBOARD DRINK ME MUG,6,1.06,17850
VINTAGE BILLBOARD LOVE/HATE MUG,6,1.06,17850
WOOD 2 DRAWER CABINET WHITE FINISH,2,4.95,17850
WOOD S/3 CABINET ANT WHITE FINISH,4,6.95,17850
WOODEN PICTURE FRAME WHITE FINISH,6,2.1,17850
WOODEN FRAME ANTIQUE WHITE ,6,2.55,17850
KNITTED UNION FLAG HOT WATER BOTTLE,6,3.39,17850
RED WOOLLY HOTTIE WHITE HEART.,6,3.39,17850
SET 7 BABUSHKA NESTING BOXES,2,7.65,17850
GLASS STAR FROSTED T-LIGHT HOLDER,6,4.25,17850
HOT WATER BOTTLE TEA AND SYMPATHY,48,3.45,15291
RED HANGING HEART T-LIGHT HOLDER,64,2.55,15291
HAND WARMER RED POLKA DOT,6,1.85,17850
HAND WARMER UNION JACK,6,1.85,17850
JUMBO BAG PINK POLKADOT,10,1.95,14688
JUMBO  BAG BAROQUE BLACK WHITE,10,1.95,14688
JUMBO BAG CHARLIE AND LOLA TOYS,10,2.95,14688
STRAWBERRY CHARLOTTE BAG,10,0.85,14688
RED 3 PIECE RETROSPOT CUTLERY SET,12,3.75,14688
BLUE 3 PIECE POLKADOT CUTLERY SET,6,3.75,14688
SET/6 RED SPOTTY PAPER PLATES,12,0.85,14688
LUNCH BAG RED RETROSPOT,10,1.65,14688
STRAWBERRY LUNCH BOX WITH CUTLERY,6,2.55,14688
LUNCH BOX WITH CUTLERY RETROSPOT ,6,2.55,14688
PACK OF 72 RETROSPOT CAKE CASES,120,0.42,14688
PACK OF 60 DINOSAUR CAKE CASES,24,0.55,14688
PACK OF 60 PINK PAISLEY CAKE CASES,24,0.55,14688
60 TEATIME FAIRY CAKE CASES,24,0.55,14688
```

This dataset was taken from the UCI Machine Learning Repository at the following website: https://archive.ics.uci.edu/dataset/502/online+retail+ii

Information about the variables of the dataset are as follows:

- Description: Product (item) name. Nominal.
- Quantity: The quantities of each product (item) per transaction. Numeric.
- Price: Unit price. Numeric. Product price per unit in sterling (Â£).
- CustomerID: Customer number. Nominal. A 5-digit integral number uniquely assigned to each customer.

Below are screenshots of the code from the python file:

- ☐ *To run the following code, the user must have or install the following packages:*
  - ☐ *NLTK*
  - ☐ *Openpyxl*
  - ☐ *Tabulate*
  - ☐ *Tensorflow*
  - ☐ *Wordcloud*

Data Mining Final Project - Saketh Lakshmanan

Pre-processing the data

```
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

# Load data from the CSV file
data = pd.read_csv('invoice_transactions.csv')

# Drop rows with missing values
data.dropna(inplace=True)

# Encode categorical variables (Description) using LabelEncoder
label_encoder = LabelEncoder()
data['Description'] = label_encoder.fit_transform(data['Description'])

# Convert 'Customer ID' to integer
data['Customer ID'] = data['Customer ID'].astype(int)

# Define features (X) and target (y)
X = data.drop('Customer ID', axis=1)  # Features: all columns except 'Customer ID'
y = data['Customer ID']  # Target variable: 'Customer ID'
```

Using the RANDOM FOREST algorithm to reccomend the top 10 products in the dataset to future customers

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE



# 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)

# Train the Random Forest classifier
clf = RandomForestClassifier()
clf.fit(X_train, y_train)

# Make predictions on the testing set
y_pred_proba = clf.predict_proba(X_test)

# Get the predicted probabilities for positive class (purchasing the product)
product_probabilities = y_pred_proba[:, 1]

# Recommend top N products for each customer
N = 10  # Number of products to recommend
top_products_indices = product_probabilities.argsort()[-N:][::-1]  # Indices of top N products
top_products = X_test.iloc[top_products_indices]  # Top N recommended products
```

Display Results

```
# Convert the 'Description' column to object dtype (string)
top_products['Description'] = top_products['Description'].astype(str)

# Invert the label encoding to get original product descriptions
reversed_description = label_encoder.inverse_transform(top_products['Description'].astype(int))

# Replace the numerical representation with the original words in the DataFrame
top_products.loc[:, 'Description'] = reversed_description

# Replace the numerical representation with the original words in the DataFrame
top_products.loc[:, 'Description'] = reversed_description

top_products_formatted = top_products.reset_index(drop=True)

# Display the recommended products
print("Top Recommended Products:")
print(top_products_formatted)
```

```
Top Recommended Products:
                         Description  Quantity  Price
0        BLUE COAT RACK PARIS FASHION         3   4.95
1            LOVE BUILDING BLOCK WORD         3   5.95
2                            POSTAGE          3  18.00
3         RED COAT RACK PARIS FASHION         3   4.95
4  BOX OF 6 ASSORTED COLOUR TEASPOONS         6   4.25
5         INFLATABLE POLITICAL GLOBE         48   0.85
6   WOODEN PICTURE FRAME WHITE FINISH         6   2.10
7             MINI PAINT SET VINTAGE         36   0.65
8        SET 7 BABUSHKA NESTING BOXES         2   7.65
9    RED HANGING HEART T-LIGHT HOLDER        64   2.55
```

10 Fold Cross Validation (for random forest)

```
from sklearn.model_selection import StratifiedKFold
from sklearn.ensemble import RandomForestClassifier
import numpy as np

# Initialize variables to store TP, TN, FP, FN
tp_random_forest = tn_random_forest = fp_random_forest = fn_random_forest = 0

# Define the cross-validation strategy
skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# Iterate over the folds
for train_index, test_index in skf.split(X, y):
    # Split data into train and test sets for this fold
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Initialize and train the Random Forest classifier
    clf = RandomForestClassifier()
    clf.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = clf.predict(X_test)

    # Update TP, TN, FP, FN counts
    for true_label, pred_label in zip(y_test, y_pred):
        if true_label == pred_label:
            if true_label == 1:
                tp_random_forest += 1
            else:
                tn_random_forest += 1
        else:
            if pred_label == 1:
                fp_random_forest += 1
            else:
                fn_random_forest += 1

tpr_random_forest = tn_random_forest/(tn_random_forest + fn_random_forest)
spc_random_forest = tn_random_forest/(fp_random_forest + tn_random_forest)
ppv_random_forest = tp_random_forest/((tp_random_forest + fp_random_forest)+1)
npv_random_forest = tn_random_forest/(tn_random_forest + fn_random_forest)
fpr_random_forest = fp_random_forest/(fp_random_forest + tn_random_forest)
fdr_random_forest = fp_random_forest/((fp_random_forest + tp_random_forest)+1)
fnr_random_forest = fn_random_forest/(fn_random_forest + tp_random_forest)
acc_random_forest = (tp_random_forest + tn_random_forest)/(tn_random_forest + tp_random_forest + tn_random_forest)
f1_random_forest = 2*tp_random_forest / (2*tp_random_forest + fp_random_forest + fn_random_forest)
tss_random_forest = (tp_random_forest/(tp_random_forest + fn_random_forest)) - (fp_random_forest/(fp_random_forest + tn_random_forest))
hss_random_forest = (2*(tp_random_forest*tn_random_forest - fp_random_forest*fn_random_forest))/(((tp_random_forest+fn_random_forest) * (f
```

Confusion Matrix Metrics Table (random forest)

```
from tabulate import tabulate

# Define the metrics
metrics_data = [
    ["TN", tn_random_forest],
    ["FP", fp_random_forest],
    ["FN", fn_random_forest],
    ["TP", tp_random_forest]
]

# Create the table
table = tabulate(metrics_data, headers=["Metric", "Value"], tablefmt="fancy_grid", numalign="center")

# Print the table
print("\nOverall Metrics (Average of 10 Folds):")
print(table)
```

```
Overall Metrics (Average of 10 Folds):
```

Metric	Value
TN	78
FP	0
FN	22
TP	0

Extra Metrics (MANUALLY CALCULATED) Table

```
# Define the extra metrics
extra_metrics_data = [
    ["TPR (True Positive Rate)", tpr_random_forest],
    ["SPC (Specificity)", spc_random_forest],
    ["PPV (Positive Predictive Value)", ppv_random_forest],
    ["NPV (Negative Predictive Value)", npv_random_forest],
    ["FPR (False Positive Rate)", fpr_random_forest],
    ["FDR (False Discovery Rate)", fdr_random_forest],
    ["FNR (False Negative Rate)", fnr_random_forest],
    ["ACC (Accuracy)", acc_random_forest],
    ["F1 score", f1_random_forest],
    ["TSS (True Skill Statistic)", tss_random_forest],
    ["HSS (Heidke Skill Score)", hss_random_forest]
]

# Create the table
table_extra_metrics = tabulate(extra_metrics_data, headers=["Metric", "Value"], tablefmt="fancy_grid", numalign="center")

# Print the table
print("\nExtra Metrics (MANUALLY DONE):")
print(table_extra_metrics)
```

```
Extra Metrics (MANUALLY DONE):
```

Metric	Value
TPR (True Positive Rate)	0.78
SPC (Specificity)	1
PPV (Positive Predictive Value)	0
NPV (Negative Predictive Value)	0.78
FPR (False Positive Rate)	0
FDR (False Discovery Rate)	0
FNR (False Negative Rate)	1
ACC (Accuracy)	0.5
F1 score	0
TSS (True Skill Statistic)	0
HSS (Heidke Skill Score)	0

Now using NAIVE BAYES to find the number of mislabeled points

```
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB

# Load the dataset
data = pd.read_csv("invoice_transactions.csv")

# Extract features and target variable
X_text = data["Description"]
X_numeric = data[["Quantity", "Price"]]
y = data["Customer ID"]

# Initialize CountVectorizer
vectorizer = CountVectorizer()

# Fit and transform the text data
X_text_bow = vectorizer.fit_transform(X_text)

# Generate generic feature names for BoW features
bow_feature_names = [f"word_{i}" for i in range(X_text_bow.shape[1])]

# Concatenate text BoW features with numeric features
X = pd.concat([pd.DataFrame(X_text_bow.toarray(), columns=bow_feature_names), X_numeric], axis=1)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=0)

# Initialize a Gaussian Naive Bayes classifier
gnb = GaussianNB()

# Fit the classifier to the training data and make predictions on the test data
y_pred = gnb.fit(X_train, y_train).predict(X_test)

# Calculate the number of mislabeled points
mislabeled_points = (y_test != y_pred).sum()
print("Number of mislabeled points out of a total %d points : %d" % (X_test.shape[0], mislabeled_points))
```

```
Number of mislabeled points out of a total 50 points : 16
```

10 Fold Cross Validation (naive bayes)

```
from sklearn.model_selection import StratifiedKFold
from sklearn.naive_bayes import GaussianNB
import numpy as np

# Define the cross-validation strategy
kf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# Initialize variables to store TP, TN, FP, FN
tp_naive = tn_naive = fp_naive = fn_naive = 0

# Perform 10-fold cross-validation
for train_index, test_index in kf.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Initialize and train Gaussian Naive Bayes classifier
    gnb = GaussianNB()
    gnb.fit(X_train, y_train)

    # Predict labels for test set
    y_pred = gnb.predict(X_test)

    # Update TP, TN, FP, FN counts
    for true_label, pred_label in zip(y_test, y_pred):
        if true_label == pred_label:
            if true_label == 1:
                tp_naive += 1
            else:
                tn_naive += 1
        else:
            if pred_label == 1:
                fp_naive += 1
            else:
                fn_naive += 1

# Calculate additional metrics
tpr_naive = tn_naive/(tn_naive + fn_naive)
spc_naive = tn_naive/(fp_naive + tn_naive)
ppv_naive = tp_naive/((tp_naive + fp_naive)+1)
npv_naive = tn_naive/(tn_naive + fn_naive)
fpr_naive = fp_naive/(fp_naive + tn_naive)
fdr_naive = fp_naive/((fp_naive + tp_naive)+1)
fnr_naive = fn_naive/(fn_naive + tp_naive)
acc_naive = (tp_naive + tn_naive)/(fp_naive + fn_naive + tn_naive)
f1_naive = 2*tp_naive / (2*tp_naive + fp_naive + fn_naive)
tss_naive = (tp_naive/(tp_naive + fn_naive)) - (fp_naive/(fp_naive + tn_naive))
hss_naive = (2*(tp_naive*tn_naive - fp_naive*fn_naive))/(((tp_naive+fn_naive) * (fn_naive+tn_naive) * (tp_naive+fp_naive) * (fp_naive+tn_n
```

Confusion Matrix Metrics Table (naive bayes) ¶

```
from tabulate import tabulate

# Define the metrics
metrics_data = [
    ["TP", tp_naive],
    ["TN", tn_naive],
    ["FP", fp_naive],
    ["FN", fn_naive]

]

# Create the table
table = tabulate(metrics_data, headers=["Metric", "Value"], tablefmt="fancy_grid", numalign="center")

# Print the table
print("\nOverall Metrics (Average of 10 Folds):")
print(table)
```

```
Overall Metrics (Average of 10 Folds):
```

Metric	Value
TP	0
TN	83
FP	0
FN	17

Extra Metrics (MANUALLY CALCULATED) Table

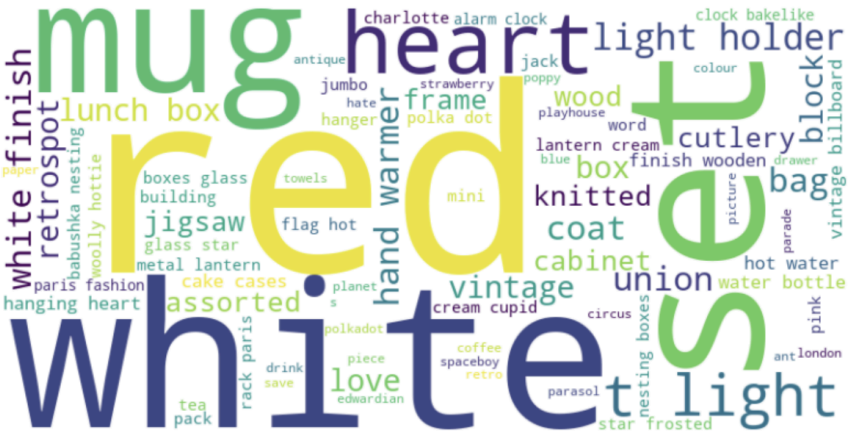
```
# Define the extra metrics
extra_metrics_data = [
    ["TPR (True Positive Rate)", tpr_naive],
    ["SPC (Specificity)", spc_naive],
    ["PPV (Positive Predictive Value)", ppv_naive],
    ["NPV (Negative Predictive Value)", npv_naive],
    ["FPR (False Positive Rate)", fpr_naive],
    ["FDR (False Discovery Rate)", fdr_naive],
    ["FNR (False Negative Rate)", fnr_naive],
    ["ACC (Accuracy)", acc_naive],
    ["F1 score", f1_naive],
    ["TSS (True Skill Statistic)", tss_naive],
    ["HSS (Heidke Skill Score)", hss_naive]
]

# Create the table
table_extra_metrics = tabulate(extra_metrics_data, headers=["Metric", "Value"], tablefmt="fancy_grid", numalign="center")

# Print the table
print("\nExtra Metrics (MANUALLY DONE):")
print(table_extra_metrics)
```

```
Extra Metrics (MANUALLY DONE):
```

Metric	Value
TPR (True Positive Rate)	0.83
SPC (Specificity)	1
PPV (Positive Predictive Value)	0
NPV (Negative Predictive Value)	0.83
FPR (False Positive Rate)	0
FDR (False Discovery Rate)	0
FNR (False Negative Rate)	1
ACC (Accuracy)	0.83
F1 score	0
TSS (True Skill Statistic)	0
HSS (Heidke Skill Score)	0

Now using CONV1D to find the most common words in the description column ¶

```
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud

# Load data from the CSV file
data = pd.read_csv('invoice_transactions.csv')

# Drop rows with missing values
data.dropna(inplace=True)

# Function to clean text
def clean_text(text):
    text = text.lower()  # Convert text to lowercase
    return text

# Apply text cleaning function to the Description column
data['Cleaned_Description'] = data['Description'].apply(clean_text)

# Join all cleaned descriptions into a single string
all_text = ' '.join(data['Cleaned_Description'].values)

# Generate word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white', min_font_size=10).generate(all_text)

# Display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```



10 Fold Cross Verification (conv1d)

```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import accuracy_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
import numpy as np
import warnings
warnings.filterwarnings("ignore")

# Define the cross-validation strategy
kf = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# Reset the index of DataFrame X
X.reset_index(drop=True, inplace=True)

# Initialize variables to store TP, TN, FP, FN
tp_conv1d = tn_conv1d = fp_conv1d = fn_conv1d = 0
tp_conv1d_total = tn_conv1d_total = fp_conv1d_total = fn_conv1d_total = 0

# Perform 10-fold cross-validation
for train_index, test_index in kf.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y[train_index], y[test_index]

    # Reshape input data
    X_train = X_train.values.reshape(X_train.shape[0], X_train.shape[1], 1)
    X_test = X_test.values.reshape(X_test.shape[0], X_test.shape[1], 1)

    # Define model architecture
    model = Sequential([
        Conv1D(64, kernel_size=3, activation='relu', input_shape=(X_train.shape[1], X_train.shape[2])),
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(64, activation='relu'),
        Dense(1, activation='sigmoid')
    ])

    # Compile model
    model.compile(optimizer=Adam(learning_rate=0.001), loss='binary_crossentropy', metrics=['accuracy'])

    # Train model
    model.fit(X_train, y_train, epochs=10, batch_size=32, verbose=0)

    # Make predictions
    y_pred = (model.predict(X_test) > 0.5).astype("int32").reshape(-1)
```

```
    # Update TP, TN, FP, FN counts
    for true_label, pred_label in zip(y_test, y_pred):
        if true_label == pred_label:
            if true_label == 1:
                tp_conv1d += 1
            else:
                tn_conv1d += 1
        else:
            if pred_label == 1:
                fp_conv1d += 1
            else:
                fn_conv1d += 1

    # Accumulate counts for each iteration
    tp_conv1d_total += tp_conv1d
    tn_conv1d_total += tn_conv1d
    fp_conv1d_total += fp_conv1d
    fn_conv1d_total += fn_conv1d

tpr_conv1d = tn_conv1d/((tn_conv1d + fn_conv1d)+1)
spc_conv1d = tn_conv1d/(fp_conv1d + tn_conv1d)
ppv_conv1d = tp_conv1d/(tp_conv1d + fp_conv1d)
npv_conv1d = tn_conv1d/((tn_conv1d + fn_conv1d)+1)
fpr_conv1d = fp_conv1d/(fp_conv1d + tn_conv1d)
fdr_conv1d = fp_conv1d/(fp_conv1d + tp_conv1d)
fnr_conv1d = fn_conv1d/((fn_conv1d + tp_conv1d)+1)
acc_conv1d = (tp_conv1d + tn_conv1d)/(fp_conv1d + fn_conv1d + tn_conv1d)
f1_conv1d = 2*tp_conv1d / (2*tp_conv1d + fp_conv1d + fn_conv1d)
tss_conv1d = (tp_conv1d/(tp_conv1d + fn_conv1d +1)) - (fp_conv1d/(fp_conv1d + tn_conv1d +1))
hss_conv1d = (2*(tp_conv1d*tn_conv1d - fp_conv1d*fn_conv1d))/((((tp_conv1d+fn_conv1d) * (fn_conv1d+tn_conv1d) + (tp_conv1d+fp_conv1d) * (fp
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
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```

Confusion Matrix Metrics Table (conv1D)

```
from tabulate import tabulate

# Define the metrics
metrics_data = [
    ["TP", tp_conv1d],
    ["TN", tn_conv1d],
    ["FP", fp_conv1d],
    ["FN", fn_conv1d]

]

# Create the table
table = tabulate(metrics_data, headers=["Metric", "Value"], tablefmt="fancy_grid", numalign="center")

# Print the table
print("\nOverall Metrics (Average of 10 Folds):")
print(table)
```

```
Overall Metrics (Average of 10 Folds):
```

Metric	Value
TP	0
TN	0
FP	100
FN	0

Extra Metrics (MANUALLY CALCULATED) Table

```
# Define the extra metrics
extra_metrics_data = [
    ["TPR (True Positive Rate)", tpr_conv1d],
    ["SPC (Specificity)", spc_conv1d],
    ["PPV (Positive Predictive Value)", ppv_conv1d],
    ["NPV (Negative Predictive Value)", npv_conv1d],
    ["FPR (False Positive Rate)", fpr_conv1d],
    ["FDR (False Discovery Rate)", fdr_conv1d],
    ["FNR (False Negative Rate)", fnr_conv1d],
    ["ACC (Accuracy)", acc_conv1d],
    ["F1 score", f1_conv1d],
    ["TSS (True Skill Statistic)", tss_conv1d],
    ["HSS (Heidke Skill Score)", hss_conv1d]
]

# Create the table
table_extra_metrics = tabulate(extra_metrics_data, headers=["Metric", "Value"], tablefmt="fancy_grid", numalign="center")

# Print the table
print("\nExtra Metrics (MANUALLY DONE):")
print(table_extra_metrics)
```

```
Extra Metrics (MANUALLY DONE):
```

Metric	Value
TPR (True Positive Rate)	0
SPC (Specificity)	0
PPV (Positive Predictive Value)	0
NPV (Negative Predictive Value)	0
FPR (False Positive Rate)	1
FDR (False Discovery Rate)	1
FNR (False Negative Rate)	0
ACC (Accuracy)	0
F1 score	0
TSS (True Skill Statistic)	-0.990099
HSS (Heidke Skill Score)	0

Total Metrics for all three algorithms

```
# Define the metrics and their corresponding values
metrics = [
    ["Metric", "Random Forest", "Naive", "Conv1D"],
    ["TP", tp_random_forest, tp_naive, tp_conv1d],
    ["TN", tn_random_forest, tn_naive, tn_conv1d],
    ["FP", fp_random_forest, fp_naive, fp_conv1d],
    ["FN", fn_random_forest, fn_naive, fn_conv1d],
    ["TPR", tpr_random_forest, tpr_naive, tpr_conv1d],
    ["SPC", spc_random_forest, spc_naive, spc_conv1d],
    ["PPV", ppv_random_forest, ppv_naive, ppv_conv1d],
    ["NPV", npv_random_forest, npv_naive, npv_conv1d],
    ["FPR", fpr_random_forest, fpr_naive, fpr_conv1d],
    ["FDR", fdr_random_forest, fdr_naive, fdr_conv1d],
    ["FNR", fnr_random_forest, fnr_naive, fnr_conv1d],
    ["ACC", acc_random_forest, acc_naive, acc_conv1d],
    ["F1", f1_random_forest, f1_naive, f1_conv1d],
    ["TSS", tss_random_forest, tss_naive, tss_conv1d],
    ["HSS", hss_random_forest, hss_naive, hss_conv1d]
]

# Print the table
print(tabulate(metrics, headers="firstrow", tablefmt="fancy_grid"))
```

Metric	Random Forest	Naive	Conv1D
TP	0	0	0
TN	78	83	0
FP	0	0	100
FN	22	17	0
TPR	0.78	0.83	0
SPC	1	1	0
PPV	0	0	0
NPV	0.78	0.83	0
FPR	0	0	1
FDR	0	0	1
FNR	1	1	0
ACC	0.5	0.83	0
F1	0	0	0
TSS	0	0	-0.990099
HSS	0	0	0

The final table compares and contrasts all metrics from all three algorithms in a tabular format:

Other

The algorithms used were taken from the following sources:

- ➢ Random Forest Algorithm
  - https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html#sklearn.ensemble.RandomForestClassifier
- ➢ Naive Bayes Algorithm
  - https://scikit-learn.org/stable/modules/naive_bayes.html#
- ➢ Conv1d Algorithm
  - https://becominghuman.ai/1-dimensional-convolution-layer-for-nlp-task-5d2e86e0229c

The source code (.py file), data sets (.csv files), and jupyter file(.ipynb file) will be attached to the zip file.

Link to Git Repository(Github account has personal email as main emailand NJIT email as secondary email):
https://github.com/sakethl20/Data-Mining-Algorithm-Metric-Calculation