Importing the necessary libraries that are needed

```
import pandas as pd
import json
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import numpy as np
from collections import Counter
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import shap
import matplotlib.pylab as pl
shap.initjs()
import torch
import torch.nn as nn
import torch.optim as optim
import copy
```

Intsalling the transformers, dataset and torch pachages that are needed for Bert Transformer

```
pip install transformers datasets torch
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.11/dist-packages (4.51.3)
Requirement already satisfied: datasets in /usr/local/lib/python3.11/dist-packages (3.5.0)
Requirement already satisfied: torch in /usr/local/lib/python3.11/dist-packages (2.6.0+cu124)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from transformers) (3.18.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.30.0 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.30.2)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.11/dist-packages (from transformers) (2.0.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.11/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.11/dist-packages (from transformers) (2024.11.6)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.21.1)
Requirement already satisfied: safetensors>=0.4.3 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.5.3)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.11/dist-packages (from transformers) (4.67.1)
Requirement already satisfied: pyarrow>=15.0.0 in /usr/local/lib/python3.11/dist-packages (from datasets) (18.1.0)
```

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Requirement already satisfied: dill<0.3.9,>=0.3.0 in /usr/local/lib/python3.11/dist-packages (from datasets) (0.3.8)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from datasets) (2.2.2)
Requirement already satisfied: xxhash in /usr/local/lib/python3.11/dist-packages (from datasets) (3.5.0)
Requirement already satisfied: multiprocess<0.70.17 in /usr/local/lib/python3.11/dist-packages (from datasets) (0.70.16)
Requirement already satisfied: fsspec<=2024.12.0,>=2023.1.0 in /usr/local/lib/python3.11/dist-packages (from fsspec[http]<=2024.12.0,>=2023.1.0->datasets)
Requirement already satisfied: aiohttp in /usr/local/lib/python3.11/dist-packages (from datasets) (3.11.15)
Requirement already satisfied: typing-extensions>=4.10.0 in /usr/local/lib/python3.11/dist-packages (from torch) (4.13.2)
Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-packages (from torch) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (from torch) (3.1.6)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.4.127 in /usr/local/lib/python3.11/dist-packages (from torch) (12.4.127)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.4.127 in /usr/local/lib/python3.11/dist-packages (from torch) (12.4.127)
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Requirement already satisfied: nvidia-cudnn-cu12==9.1.0.70 in /usr/local/lib/python3.11/dist-packages (from torch) (9.1.0.70)
Requirement already satisfied: nvidia-cublas-cu12==12.4.5.8 in /usr/local/lib/python3.11/dist-packages (from torch) (12.4.5.8)
Requirement already satisfied: nvidia-cufft-cu12==11.2.1.3 in /usr/local/lib/python3.11/dist-packages (from torch) (11.2.1.3)
Requirement already satisfied: nvidia-curand-cu12==10.3.5.147 in /usr/local/lib/python3.11/dist-packages (from torch) (10.3.5.147)
Requirement already satisfied: nvidia-cusolver-cu12==11.6.1.9 in /usr/local/lib/python3.11/dist-packages (from torch) (11.6.1.9)
Requirement already satisfied: nvidia-cusparse-cu12==12.3.1.170 in /usr/local/lib/python3.11/dist-packages (from torch) (12.3.1.170)
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.2 in /usr/local/lib/python3.11/dist-packages (from torch) (0.6.2)
Requirement already satisfied: nvidia-nccl-cu12==2.21.5 in /usr/local/lib/python3.11/dist-packages (from torch) (2.21.5)
Requirement already satisfied: nvidia-nvtx-cu12==12.4.127 in /usr/local/lib/python3.11/dist-packages (from torch) (12.4.127)
Requirement already satisfied: nvidia-nvjitlink-cu12==12.4.127 in /usr/local/lib/python3.11/dist-packages (from torch) (12.4.127)
Requirement already satisfied: triton==3.2.0 in /usr/local/lib/python3.11/dist-packages (from torch) (3.2.0)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.11/dist-packages (from torch) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from sympy==1.13.1->torch) (1.3.0)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (2.6.1)
Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (1.3.2)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (25.3.0)
Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (1.5.0)
Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (6.4.3)
Requirement already satisfied: propcache>=0.2.0 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (0.3.1)
Requirement already satisfied: yarl<2.0,>=1.17.0 in /usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (1.19.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (2025.1.31)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2->torch) (3.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas->datasets) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas->datasets) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas->datasets) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas->datasets) (1.17.0)
```

```
pip install transformers --upgrade
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.11/dist-packages (4.51.3)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from transformers) (3.18.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.30.0 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.30.2)
```

```
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.11/dist-packages (from transformers) (2.0.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.11/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.11/dist-packages (from transformers) (2024.11.6)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.21.1)
Requirement already satisfied: safetensors>=0.4.3 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.5.3)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.11/dist-packages (from transformers) (4.67.1)
Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub<1.0,>=0.30.0->transformers) (2024.12.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.11/dist-packages (from huggingface-hub<1.0,>=0.30.0->transformers) (4.
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests->transformers) (2025.1.31)
```

Importing More Libraries of Tensorflow for the neural network model

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report
from tensorflow.keras.callbacks import EarlyStopping
import numpy as np
```

importing the libraries that are used in the Bert Transformer

```
import pandas as pd
import torch
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from transformers import BertTokenizer, BertForSequenceClassification, Trainer, TrainingArguments
from datasets import Dataset
import numpy as np
```

Loading the full dataset for Bert

```
# Load full dataset for BERT
file_path = "/content/labeled_resume_dataset_noised.xlsx"
df = pd.read_excel(file_path)

# Drop unnecessary columns
df = df.drop(columns=['FirstName', 'LastName', 'Location', 'ZipCode', 'Bilingual'], errors='ignore')

# Fill missing values
df.fillna("Unknown", inplace=True)

# Combine relevant text fields for BERT input
df['text'] = df['JobTitle'] + " " + df['Bachelors'] + " " + df['Masters'] + " " + df['JobArea'] + " " + df['EstimatedEthnicity'] + " " + df['EstimatedGender']


# Encode target labels
label_encoder = LabelEncoder()
df['label'] = label_encoder.fit_transform(df['Bias_Label'])

# Split dataset (70% train, 30% test)
train_dataframe, test_dataframe = train_test_split(df[['text', 'label']], test_size=0.3, random_state=42, stratify=df['label'])

print(f"Train set size: {train_dataframe.shape}, Test set size: {test_dataframe.shape}")
```

```
Train set size: (134, 2), Test set size: (58, 2)
```

Loading the test and train datasets for the all remainig five models

```
import pandas as pd

# Load the datasets
test_file_path = "/content/labeled_resume_dataset_test_noised.xlsx"
train_file_path = "/content/labeled_resume_dataset_train.xlsx"

train_df = pd.read_excel(train_file_path)
test_df = pd.read_excel(test_file_path)

# Display basic information
print("Training Data Info:")
print(train_df.info())

print("\nTesting Data Info:")
print(test_df.info())
```

```
# Display first few rows
print("\nTraining Data Sample:")
print(train_df.head())
```

```
Training Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192 entries, 0 to 191
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   FirstName           192 non-null    object
 1   LastName            192 non-null    object
 2   EstimatedEthnicity  192 non-null    object
 3   EstimatedGender     192 non-null    object
 4   JobTitle            192 non-null    object
 5   JobArea             192 non-null    object
 6   Bachelors           192 non-null    object
 7   Masters             93 non-null     object
 8   Location            192 non-null    object
 9   ZipCode             182 non-null    float64
 10  Bilingual           46 non-null     object
 11  Bias_Label          192 non-null    object
dtypes: float64(1), object(11)
memory usage: 18.1+ KB
None

Testing Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49 entries, 0 to 48
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   FirstName           49 non-null     object
 1   LastName            49 non-null     object
 2   EstimatedEthnicity  49 non-null     object
 3   EstimatedGender     49 non-null     object
 4   JobTitle            49 non-null     object
 5   JobArea             49 non-null     object
 6   Bachelors           49 non-null     object
 7   Masters             21 non-null     object
 8   Location            49 non-null     object
 9   ZipCode             34 non-null     float64
 10  Bilingual           8 non-null      object
 11  Bias_Label          49 non-null     object
dtypes: float64(1), object(11)
memory usage: 4.7+ KB
```

```
None

Training Data Sample:
  FirstName LastName EstimatedEthnicity EstimatedGender           JobTitle  \
0      Kurt  Schultz              White            Male  Marketing Manager
1      Kurt  Schultz              White            Male  Financial Analyst
2      Kurt  Schultz              White            Male  Marketing Manager
3      Kurt  Schultz              White            Male  Marketing Manager
4      Kurt  Schultz              White            Male  Software Engineer

                JobArea                  Bachelors               Masters  \
0             Marketing                       UCLA                   NaN
1               Finance          DePaul University                   NaN
2             Marketing  Portland State University  University of Oregon
3             Marketing                       UCLA              Stanford
```

Droping the not used columns and filling up the missing values

```
# Drop non-relevant columns
#train_df = train_df.drop(columns=['FirstName', 'LastName','JobTitle','Bachelors', 'Masters', 'Location', 'ZipCode', 'Bilingual'])
train_df = train_df.drop(columns=['FirstName', 'LastName','Location', 'ZipCode', 'Bilingual'])
#test_df = test_df.drop(columns=['FirstName', 'LastName','JobTitle','Bachelors', 'Masters', 'Location', 'ZipCode', 'Bilingual'])
test_df = test_df.drop(columns=['FirstName', 'LastName','Location', 'ZipCode', 'Bilingual'])

# Fill missing values with "Unknown"
train_df.fillna("Unknown", inplace=True)
test_df.fillna("Unknown", inplace=True)

# Verify if all missing values are handled
print("\nMissing Values After Cleaning:")
print(train_df.isnull().sum())
```

```
Missing Values After Cleaning:
EstimatedEthnicity    0
EstimatedGender       0
JobTitle              0
JobArea               0
Bachelors             0
Masters               0
Bias_Label            0
dtype: int64
```

Loading the Tokenizer that is used for Bert

```
# Load BERT tokenizer
tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")

# Tokenization function
def tokenize_function(data):
    return tokenizer(data["text"], padding="max_length", truncation=True, max_length=128)

# Convert Pandas DataFrame to Hugging Face Dataset
train_dataset = Dataset.from_pandas(train_dataframe)
test_dataset = Dataset.from_pandas(test_dataframe)

# Apply tokenization
train_dataset = train_dataset.map(tokenize_function, batched=True)
test_dataset = test_dataset.map(tokenize_function, batched=True)
```

```
Map: 100%    134/134 [00:00<00:00, 796.47 examples/s]

Map: 100%    58/58 [00:00<00:00, 344.35 examples/s]
```

Seeing all the unquie Job Areas that are avialable in the dataset

```
# Get the unique values of 'B' column
unique_values = train_df['JobArea'].unique()
unique_values_train = test_df['JobArea'].unique()

# Print the unique values
print("\nUnique values in JobArea column:")
print(unique_values)
print(unique_values_train)
```

```
Unique values in JobArea column:
['Marketing' 'Finance' 'Software Engineering' 'Project Management' 'Sales'
 'Mechanical Engineering']
['Software Engineering' 'Marketing' 'Project Management' 'Finance'
 'Nursing']
```

Encoding into categorical data using the One Hot Encoder

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.feature_extraction.text import TfidfVectorizer
from scipy.sparse import hstack

# Ensure column names are stripped of whitespace
train_df.columns = train_df.columns.str.strip()
test_df.columns = test_df.columns.str.strip()


# Define categorical & text features
categorical_features = ['EstimatedEthnicity', 'EstimatedGender', 'JobArea']
text_features = ['JobTitle', 'Bachelors', 'Masters']

ohe = OneHotEncoder(handle_unknown='ignore', sparse_output=True)  # Ensuring consistency
ohe.fit(train_df[categorical_features])

ohe = OneHotEncoder(handle_unknown='ignore', sparse_output=True)  # Ensuring consistency
ohe.fit(train_df[categorical_features])  # Fit on training data only

X_train_cat = ohe.transform(train_df[categorical_features])
X_test_cat = ohe.transform(test_df[categorical_features])  # Use transform (not fit_transform)

print(f" One-Hot Encoding - Train Shape: {X_train_cat.shape}, Test Shape: {X_test_cat.shape}")
```

```
One-Hot Encoding - Train Shape: (192, 12), Test Shape: (49, 12)
```

Using the Tf-Idf for vectorization of Text Features

```
tfidf = TfidfVectorizer(max_features=100)  # Ensure consistent max features

tfidf.fit(train_df['JobTitle'] + " " + train_df['Bachelors'] + " " + train_df['Masters'])  # Fit TF-IDF on combined train text

X_train_text = hstack([tfidf.transform(train_df[col]) for col in text_features])
X_test_text = hstack([tfidf.transform(test_df[col]) for col in text_features])  # Only transform test data

print(f" TF-IDF - Train Shape: {X_train_text.shape}, Test Shape: {X_test_text.shape}")
```

```
TF-IDF - Train Shape: (192, 258), Test Shape: (49, 258)
```

Combing the text and categorical features into final test and train sets

```
# Combine all features
X_train = hstack([X_train_cat, X_train_text])
X_test = hstack([X_test_cat, X_test_text])

print(f" Final Feature Shapes - Train: {X_train.shape}, Test: {X_test.shape}")

# Verify if feature mismatch still exists
if X_train.shape[1] != X_test.shape[1]:
    print(f" Feature mismatch! Train has {X_train.shape[1]} features, Test has {X_test.shape[1]}")
else:
    print(" Feature count matches!")
```

```
 Final Feature Shapes - Train: (192, 270), Test: (49, 270)
 Feature count matches!
```

```
from sklearn.preprocessing import LabelEncoder

# Convert Bias_Label column to numeric
label_encoder = LabelEncoder()
y_train = label_encoder.fit_transform(train_df['Bias_Label'])
y_test = label_encoder.transform(test_df['Bias_Label'])

print("Target variable converted successfully!")
print(f"Unique values in y_train: {set(y_train)}")
print(f"Unique values in y_test: {set(y_test)}")
```

```
Target variable converted successfully!
Unique values in y_train: {np.int64(0), np.int64(1)}
Unique values in y_test: {np.int64(0), np.int64(1)}
```

The first model used is the random forest model

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Train Random Forest Model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Predictions
y_pred_rf = rf.predict(X_test)
```

```
# Evaluation
print("Random Forest Performance:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Performance:
              precision    recall  f1-score   support

           0       0.79      0.55      0.65        20
           1       0.74      0.90      0.81        29

    accuracy                           0.76        49
   macro avg       0.76      0.72      0.73        49
weighted avg       0.76      0.76      0.74        49
```

The second model used is the XGBoost model

```
from xgboost import XGBClassifier
from sklearn.metrics import classification_report

# Train XGBoost Model (Without use_label_encoder)
xgb = XGBClassifier(eval_metric='logloss')
xgb.fit(X_train, y_train)

# Predictions
y_pred_xgb = xgb.predict(X_test)

# Evaluation
print("XGBoost Performance:")
print(classification_report(y_test, y_pred_xgb))
```

```
XGBoost Performance:
              precision    recall  f1-score   support

           0       0.61      0.55      0.58        20
           1       0.71      0.76      0.73        29

    accuracy                           0.67        49
   macro avg       0.66      0.65      0.66        49
weighted avg       0.67      0.67      0.67        49
```

The third model used is the MLP(mutli level perceptron) Classifier model

```
from sklearn.neural_network import MLPClassifier

# Train MLP Neural Network
mlp = MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=500, random_state=42)
mlp.fit(X_train, y_train)

# Predictions
y_pred_mlp = mlp.predict(X_test)

# Evaluation
print("Neural Network Performance:")
print(classification_report(y_test, y_pred_mlp))
```

```
Neural Network Performance:
              precision    recall  f1-score   support

           0       0.69      0.55      0.61        20
           1       0.73      0.83      0.77        29

    accuracy                           0.71        49
   macro avg       0.71      0.69      0.69        49
weighted avg       0.71      0.71      0.71        49
```

The fourth model used is the custom built model with three layer and with relu activation function

```
# Define the model
model = Sequential([
    Dense(256, activation='relu', input_shape=(X_train.shape[1],)),  # Input Layer
    Dropout(0.4),  # Prevent overfitting
    Dense(128, activation='relu'),  # Hidden Layer 1
    Dropout(0.3),
    Dense(64, activation='relu'),  # Hidden Layer 2
    Dense(1, activation='sigmoid')  # Output Layer (Binary Classification)
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0005),
              loss='binary_crossentropy',
```

```
              metrics=['accuracy'])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Training the custom built model

```
# Train the model
history = model.fit(X_train.toarray(), y_train,  # Convert sparse matrix to array
                    epochs=100, batch_size=32,
                    validation_data=(X_test.toarray(), y_test),
                    verbose=1)

early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
```

```
Epoch 1/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 4s 115ms/step - accuracy: 0.4531 - loss: 0.7053 - val_accuracy: 0.6122 - val_loss: 0.6626
Epoch 2/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.6726 - loss: 0.6547 - val_accuracy: 0.5918 - val_loss: 0.6447
Epoch 3/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - accuracy: 0.6775 - loss: 0.6254 - val_accuracy: 0.5918 - val_loss: 0.6318
Epoch 4/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - accuracy: 0.6655 - loss: 0.6202 - val_accuracy: 0.6122 - val_loss: 0.6196
Epoch 5/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - accuracy: 0.6946 - loss: 0.5965 - val_accuracy: 0.7143 - val_loss: 0.6040
Epoch 6/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - accuracy: 0.7449 - loss: 0.5619 - val_accuracy: 0.7347 - val_loss: 0.5908
Epoch 7/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - accuracy: 0.7846 - loss: 0.5399 - val_accuracy: 0.7347 - val_loss: 0.5795
Epoch 8/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - accuracy: 0.7565 - loss: 0.5073 - val_accuracy: 0.7347 - val_loss: 0.5660
Epoch 9/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - accuracy: 0.8120 - loss: 0.4590 - val_accuracy: 0.7347 - val_loss: 0.5588
Epoch 10/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 0.8054 - loss: 0.4400 - val_accuracy: 0.7347 - val_loss: 0.5523
Epoch 11/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 65ms/step - accuracy: 0.8214 - loss: 0.4073 - val_accuracy: 0.7347 - val_loss: 0.5569
Epoch 12/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 54ms/step - accuracy: 0.8318 - loss: 0.3800 - val_accuracy: 0.7347 - val_loss: 0.5615
Epoch 13/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 64ms/step - accuracy: 0.8667 - loss: 0.3395 - val_accuracy: 0.7755 - val_loss: 0.5721
Epoch 14/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 98ms/step - accuracy: 0.8345 - loss: 0.3460 - val_accuracy: 0.7755 - val_loss: 0.5933
Epoch 15/100
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step - accuracy: 0.8722 - loss: 0.2995 - val_accuracy: 0.7959 - val_loss: 0.6178
Epoch 16/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - accuracy: 0.9142 - loss: 0.2523 - val_accuracy: 0.7755 - val_loss: 0.6545
Epoch 17/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - accuracy: 0.8801 - loss: 0.2494 - val_accuracy: 0.7755 - val_loss: 0.6691
Epoch 18/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - accuracy: 0.8814 - loss: 0.2603 - val_accuracy: 0.7755 - val_loss: 0.6878
Epoch 19/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step - accuracy: 0.9059 - loss: 0.2136 - val_accuracy: 0.7551 - val_loss: 0.7126
Epoch 20/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - accuracy: 0.9256 - loss: 0.2021 - val_accuracy: 0.7551 - val_loss: 0.7315
Epoch 21/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step - accuracy: 0.9272 - loss: 0.2157 - val_accuracy: 0.7347 - val_loss: 0.7515
Epoch 22/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - accuracy: 0.9198 - loss: 0.1951 - val_accuracy: 0.7551 - val_loss: 0.7736
Epoch 23/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step - accuracy: 0.9693 - loss: 0.1563 - val_accuracy: 0.7551 - val_loss: 0.7891
Epoch 24/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step - accuracy: 0.9089 - loss: 0.1852 - val_accuracy: 0.7755 - val_loss: 0.8086
Epoch 25/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - accuracy: 0.9247 - loss: 0.1886 - val_accuracy: 0.7551 - val_loss: 0.8262
Epoch 26/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.9001 - loss: 0.1813 - val_accuracy: 0.7551 - val_loss: 0.8380
Epoch 27/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - accuracy: 0.9432 - loss: 0.1410 - val_accuracy: 0.7551 - val_loss: 0.8576
Epoch 28/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step - accuracy: 0.9538 - loss: 0.1168 - val_accuracy: 0.7551 - val_loss: 0.8741
Epoch 29/100
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 63ms/step - accuracy: 0.9457 - loss: 0.1303 - val_accuracy: 0.7551 - val_loss: 0.8882
```

Evaluating the Custom Built model

```
# Evaluate on test data
test_loss, test_acc = model.evaluate(X_test.toarray(), y_test)
print(f"\n Test Accuracy: {test_acc:.4f}")

# Make predictions
y_pred_nn = (model.predict(X_test.toarray()) > 0.5).astype(int)

# Classification Report
print("Neural Network Performance:")
print(classification_report(y_test, y_pred_nn))
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - accuracy: 0.7190 - loss: 1.5875

 Test Accuracy: 0.7347
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step
Neural Network Performance:
              precision    recall  f1-score   support

           0       0.71      0.60      0.65        20
           1       0.75      0.83      0.79        29

    accuracy                           0.73        49
   macro avg       0.73      0.71      0.72        49
weighted avg       0.73      0.73      0.73        49
```

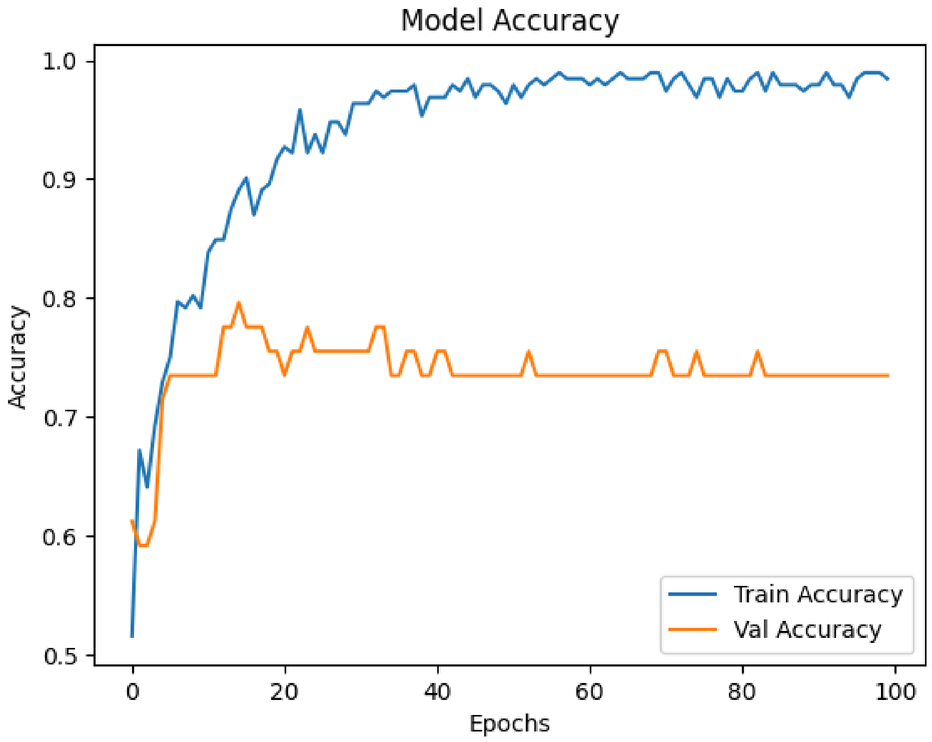
Visualization

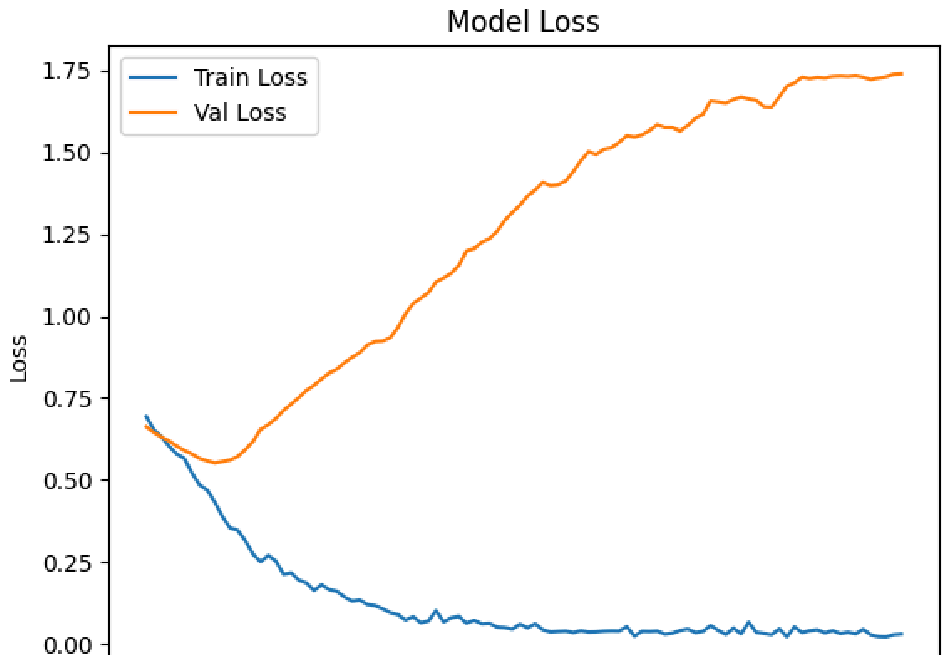
To show the accuracy and loss for train and validation

```
import matplotlib.pyplot as plt

# Plot accuracy
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title("Model Accuracy")
plt.show()

# Plot loss
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title("Model Loss")
plt.show()
```


Model Accuracy
Accuracy
Epochs
Train Accuracy
Val Accuracy
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100


Model Loss
Loss
Train Loss
Val Loss
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00

Load and train the Bert Model trainer. here we need wamdb.ai api key for using the Bert Tranformer

```
from transformers import (
    BertForSequenceClassification,
    Trainer,
    TrainingArguments,
    EarlyStoppingCallback,
    DataCollatorWithPadding
)
from sklearn.metrics import accuracy_score, f1_score
import torch

# --- Configuration ---
MODEL_NAME = "bert-base-uncased"
NUM_LABELS = 2
BATCH_SIZE = 16
MAX_LENGTH = 512

# --- Model Loading ---
model = BertForSequenceClassification.from_pretrained(
    MODEL_NAME,
    num_labels=NUM_LABELS,
    ignore_mismatched_sizes=True  # Silences classifier weight warnings
)

# --- Fixed Training Arguments ---
training_args = TrainingArguments(
    output_dir="./bert_results",
    eval_strategy="steps",
    save_strategy="steps",
    eval_steps=500,
    save_steps=500,
    learning_rate=2e-5,
    per_device_train_batch_size=BATCH_SIZE,
    per_device_eval_batch_size=BATCH_SIZE*2,
    num_train_epochs=3,
    weight_decay=0.01,
    logging_dir="./logs",
    logging_steps=50,
```

```
    load_best_model_at_end=True,
    metric_for_best_model="f1",
    fp16=torch.cuda.is_available(),
    gradient_accumulation_steps=2,
    warmup_ratio=0.1,
    report_to="none",
    optim="adamw_torch",
    dataloader_num_workers=2,     # Added for data loading optimization
    remove_unused_columns=True    # Reduces memory usage
)

data_collator = DataCollatorWithPadding(
    tokenizer=tokenizer,
    padding="longest",
    max_length=MAX_LENGTH,
    pad_to_multiple_of=8
)

def compute_metrics(pred):
    labels = pred.label_ids
    preds = pred.predictions.argmax(-1)
    return {
        "accuracy": accuracy_score(labels, preds),
        "f1": f1_score(labels, preds, average="weighted")
    }

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=test_dataset,
    data_collator=data_collator,
    compute_metrics=compute_metrics,
    callbacks=[EarlyStoppingCallback(early_stopping_patience=2)]
)

if torch.cuda.is_available():
    model = model.to("cuda")

trainer.train()
```

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are newly initialized: ['classifier.
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

[12/12 08:33, Epoch 2/3]

Step	Training Loss	Validation Loss

```
TrainOutput(global_step=12, training_loss=0.5650905768076578, metrics={'train_runtime': 563.1276, 'train_samples_per_second': 0.714,
'train_steps_per_second': 0.021, 'total_flos': 21838217594880.0, 'train_loss': 0.5650905768076578, 'epoch': 2.4444444444444446})
```

n

```
# Evaluate the model
results = trainer.evaluate()
print("Model Evaluation:", results)

# Make predictions
predictions = trainer.predict(test_dataset)

# Convert logits to labels
pred_labels = np.argmax(predictions.predictions, axis=1)

# Print classification report
from sklearn.metrics import classification_report
print("BERT Model Performance:")
print(classification_report(test_dataframe['label'], pred_labels))
```

```
Model Evaluation: {'eval_loss': 0.5092952251434326, 'eval_accuracy': 0.8103448275862069, 'eval_f1': 0.801945181255526, 'eval_runtime': 25.3019, 'eval_samp
BERT Model Performance:
              precision    recall  f1-score   support

           0       0.88      0.61      0.72        23
           1       0.79      0.94      0.86        35

    accuracy                           0.81        58
   macro avg       0.83      0.78      0.79        58
weighted avg       0.82      0.81      0.80        58
```

Start coding or generate with AI.