AI-Powered Resume Screening

April 8, 2025

0.1 AI-Powered Resume Screening

1 Let's first load the required Python libraries for data analysis and visualization.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import nltk
import pickle
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from wordcloud import WordCloud
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical
```

2 Load the Resume Dataset and explore its structure

[3]:
```
df = pd.read_csv('UpdatedResumeDataSet.csv')
```

3 Let's take a look at the data to understand its structure

[5]:
```
df.head()
```

[5]:
```
      Category                                             Resume
0  Data Science  Skills * Programming Languages: Python (pandas…
1  Data Science  Education Details \r\nMay 2013 to May 2017 B.E…
2  Data Science  Areas of Interest Deep Learning, Control Syste…
3  Data Science  Skills â ¢ R â ¢ Python â ¢ SAP HANA â ¢ Table…
4  Data Science  Education Details \r\n MCA   YMCAUST,  Faridab…
```

4 Project Title: AI-Powered Resume Screening

4.1 Problem Statement

Recruiters receive thousands of resumes, making it difficult to manually screen and match the right candidates to job roles. Our goal is to automate this process by building a resume screening system using NLP and ML techniques to classify resumes into suitable job categories.

4.2 Objective

To create an AI-driven system that can: - Automatically classify resumes into predefined categories. - Extract and visualize key insights from resumes. - Be deployed for real-time resume screening and matching.

4.3 Tools & Technologies Used

- **Programming Language:** Python
- **Data Handling & EDA:** Pandas, NumPy, Matplotlib, Seaborn
- **NLP:** NLTK, Regular Expressions, WordCloud
- **ML Model:** Naive Bayes, TF-IDF Vectorizer
- **Deep Learning:** TensorFlow, Keras, PyTorch (optional and advanced)
- **Model Evaluation:** Accuracy Score, Confusion Matrix, Classification Report
- **Deployment:** Flask (for real-world backend API)

4.4 Dataset Overview

- **Dataset Name:** UpdatedResumeDataSet.csv
- **Total Rows:** 962
- **Total Columns:** 2
  - `Category`: The job role/category (target variable)
  - `Resume`: The resume content (input feature)

4.5 Final Deliverables

Module	Description
Resume Classifier	ML/DL Model that classifies resumes into job categories
Flask App on localhost	Web API to upload & predict resume category

Module	Description
Resume Insights	Basic analytics (category-wise distribution, word clouds, etc.)
Deployment Ready	Flask app + model pickle + .py files + README

5 In this step, we clean and prepare the resume texts for model training.

We'll perform:

Removing HTML tags, Removing special characters, Converting to lowercase,Removing stop-words,Tokenization and Lemmatization

[9]:
```
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')
# Function to clean the resume text
def clean_resume(text):
    # Remove HTML tags
    text = re.sub(r'<[^>]*>', '', text)
    # Remove non-alphabetical characters and convert to lowercase
    text = re.sub(r'[^a-zA-Z]', ' ', text)
    text = text.lower()
    # Tokenize
    tokens = word_tokenize(text)
    # Remove stopwords
    tokens = [word for word in tokens if word not in stopwords.words('english')␣
↪and len(word) > 2]
    #Lemmatization
    lemmatizer = WordNetLemmatizer()
    tokens = [lemmatizer.lemmatize(word) for word in tokens]
    # Join tokens back to text
    return ' '.join(tokens)

# Apply the cleaning function to the Resume column
df['Cleaned_Resume'] = df['Resume'].apply(clean_resume)

# Display cleaned data
df[['Resume', 'Cleaned_Resume']].head(2)
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\91951\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[9]:
```
                                              Resume  \
0  Skills * Programming Languages: Python (pandas…
1  Education Details \r\nMay 2013 to May 2017 B.E…
```

```
                                       Cleaned_Resume
0  skill programming language python panda numpy …
1  education detail may may uit rgpv data scienti…
```

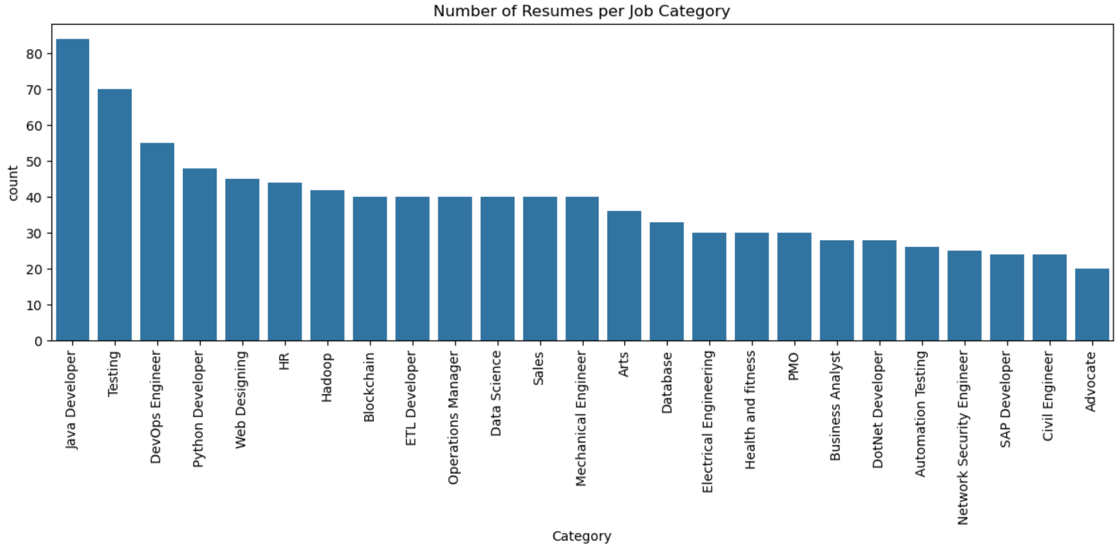
6 Now let's explore our dataset by analyzing and visualizing:

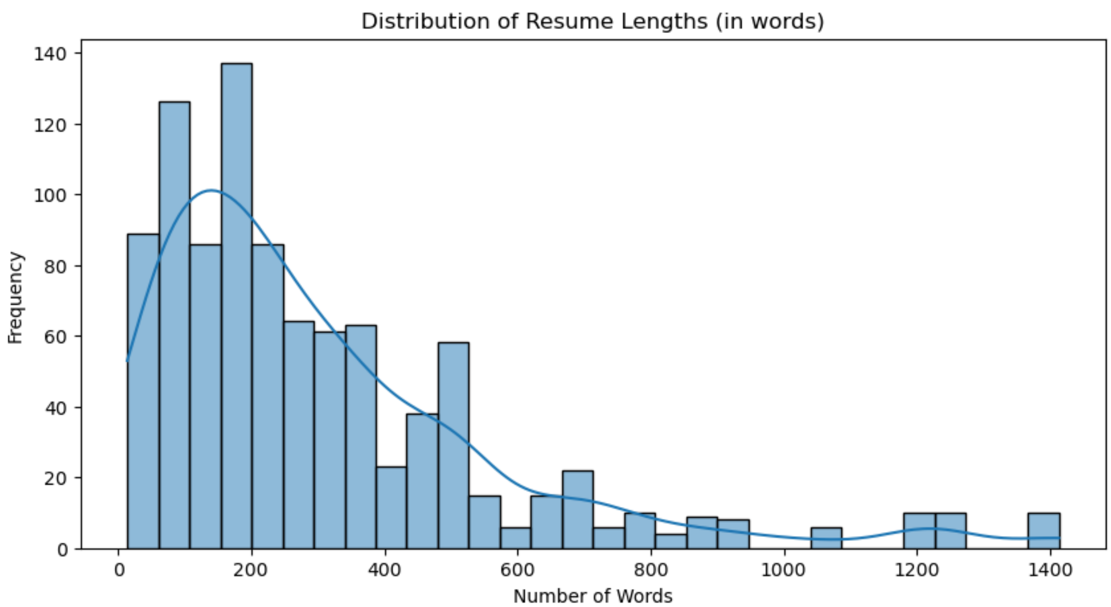
Number of resumes per job category

Distribution of resume lengths

Most common words per category using WordCloud

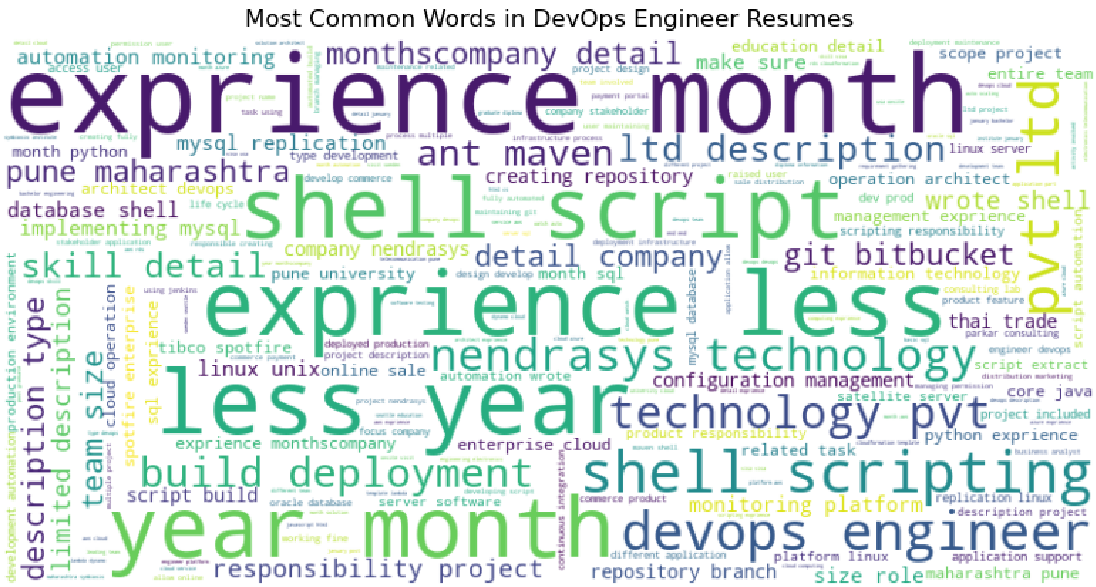
[11]:
```python
# 1. Number of resumes per category
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='Category', order=df['Category'].value_counts().index)
plt.title('Number of Resumes per Job Category')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()

# 2. Distribution of resume lengths
df['Resume_Length'] = df['Cleaned_Resume'].apply(lambda x: len(x.split()))
plt.figure(figsize=(10, 5))
sns.histplot(df['Resume_Length'], bins=30, kde=True)
plt.title('Distribution of Resume Lengths (in words)')
plt.xlabel('Number of Words')
plt.ylabel('Frequency')
plt.show()

# 3. WordCloud for top 3 categories
top_categories = df['Category'].value_counts().head(3).index
for category in top_categories:
    text = ' '.join(df[df['Category'] == category]['Cleaned_Resume'])
    wc = WordCloud(width=800, height=400, background_color='white').
 ↪generate(text)
    plt.figure(figsize=(10, 5))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Most Common Words in {category} Resumes')
    plt.show()
```


Number of Resumes per Job Category
count
0
10
20
30
40
50
60
70
80
Java Developer
Testing
DevOps Engineer
Python Developer
Web Designing
HR
Hadoop
Blockchain
ETL Developer
Operations Manager
Data Science
Sales
Mechanical Engineer
Arts
Database
Electrical Engineering
Health and fitness
PMO
Business Analyst
DotNet Developer
Automation Testing
Network Security Engineer
SAP Developer
Civil Engineer
Advocate
Category


Distribution of Resume Lengths (in words)
Frequency
0
20
40
60
80
100
120
140
0
200
400
600
800
1000
1200
1400
Number of Words

Most Common Words in Java Developer Resumes

Most Common Words in Testing Resumes



6.0.1 Feature Extraction using TF-IDF

[13]:
```python
# Transform the cleaned resume texts into numerical features
vectorizer = TfidfVectorizer(max_features=3000)
X = vectorizer.fit_transform(df['Cleaned_Resume'])
y = df['Category']
```

7 Model Building and Evaluation (Traditional ML)

[15]:
```python
# 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)

# Hyperparameter tuning for Random Forest using GridSearchCV
rf_params = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
}
rf_grid = GridSearchCV(RandomForestClassifier(), rf_params, cv=3, n_jobs=-1, verbose=1)
rf_grid.fit(X_train, y_train)
print("Best Random Forest Parameters:", rf_grid.best_params_)

# Train and evaluate tuned Random Forest
rf_model = rf_grid.best_estimator_
```

```
y_pred_rf = rf_model.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))

# Save Random Forest Model
with open('random_forest_model.pkl', 'wb') as f:
    pickle.dump(rf_model, f)

# Logistic Regression with GridSearchCV
lr_params = {'C': [0.1, 1, 10], 'solver': ['lbfgs']}
lr_grid = GridSearchCV(LogisticRegression(max_iter=1000), lr_params, cv=3,␣
 ↪n_jobs=-1, verbose=1)
lr_grid.fit(X_train, y_train)
print("Best Logistic Regression Parameters:", lr_grid.best_params_)

lr_model = lr_grid.best_estimator_
y_pred_lr = lr_model.predict(X_test)
print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_lr))
print(classification_report(y_test, y_pred_lr))

with open('logistic_regression_model.pkl', 'wb') as f:
    pickle.dump(lr_model, f)

# SVM with GridSearchCV
svm_params = {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']}
svm_grid = GridSearchCV(SVC(), svm_params, cv=3, n_jobs=-1, verbose=1)
svm_grid.fit(X_train, y_train)
print("Best SVM Parameters:", svm_grid.best_params_)

svm_model = svm_grid.best_estimator_
y_pred_svm = svm_model.predict(X_test)
print("SVM Accuracy:", accuracy_score(y_test, y_pred_svm))
print(classification_report(y_test, y_pred_svm))

with open('svm_model.pkl', 'wb') as f:
    pickle.dump(svm_model, f)

# Naive Bayes (no tuning needed for basic model)
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)
y_pred_nb = nb_model.predict(X_test)
print("Naive Bayes Accuracy:", accuracy_score(y_test, y_pred_nb))
print(classification_report(y_test, y_pred_nb))

with open('naive_bayes_model.pkl', 'wb') as f:
    pickle.dump(nb_model, f)
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
```

```
Best Random Forest Parameters: {'max_depth': None, 'min_samples_split': 5,
'n_estimators': 100}
Random Forest Accuracy: 1.0
                          precision    recall  f1-score   support

                 Advocate       1.00      1.00      1.00         3
                     Arts       1.00      1.00      1.00         6
       Automation Testing       1.00      1.00      1.00         5
               Blockchain       1.00      1.00      1.00         7
         Business Analyst       1.00      1.00      1.00         4
           Civil Engineer       1.00      1.00      1.00         9
             Data Science       1.00      1.00      1.00         5
                 Database       1.00      1.00      1.00         8
          DevOps Engineer       1.00      1.00      1.00        14
         DotNet Developer       1.00      1.00      1.00         5
            ETL Developer       1.00      1.00      1.00         7
   Electrical Engineering       1.00      1.00      1.00         6
                       HR       1.00      1.00      1.00        12
                   Hadoop       1.00      1.00      1.00         4
       Health and fitness       1.00      1.00      1.00         7
           Java Developer       1.00      1.00      1.00        15
      Mechanical Engineer       1.00      1.00      1.00         8
Network Security Engineer       1.00      1.00      1.00         3
       Operations Manager       1.00      1.00      1.00        12
                      PMO       1.00      1.00      1.00         7
         Python Developer       1.00      1.00      1.00        10
            SAP Developer       1.00      1.00      1.00         7
                    Sales       1.00      1.00      1.00         8
                  Testing       1.00      1.00      1.00        16
            Web Designing       1.00      1.00      1.00         5

                 accuracy                           1.00       193
                macro avg       1.00      1.00      1.00       193
             weighted avg       1.00      1.00      1.00       193

Fitting 3 folds for each of 3 candidates, totalling 9 fits
Best Logistic Regression Parameters: {'C': 10, 'solver': 'lbfgs'}
Logistic Regression Accuracy: 0.9948186528497409
                          precision    recall  f1-score   support

                 Advocate       1.00      1.00      1.00         3
                     Arts       1.00      1.00      1.00         6
       Automation Testing       1.00      1.00      1.00         5
               Blockchain       1.00      1.00      1.00         7
         Business Analyst       1.00      1.00      1.00         4
           Civil Engineer       1.00      1.00      1.00         9
             Data Science       1.00      1.00      1.00         5
                 Database       1.00      1.00      1.00         8
```

DevOps Engineer	1.00	0.93	0.96	14
DotNet Developer	1.00	1.00	1.00	5
ETL Developer	1.00	1.00	1.00	7
Electrical Engineering	1.00	1.00	1.00	6
HR	1.00	1.00	1.00	12
Hadoop	1.00	1.00	1.00	4
Health and fitness	1.00	1.00	1.00	7
Java Developer	1.00	1.00	1.00	15
Mechanical Engineer	1.00	1.00	1.00	8
Network Security Engineer	1.00	1.00	1.00	3
Operations Manager	1.00	1.00	1.00	12
PMO	0.88	1.00	0.93	7
Python Developer	1.00	1.00	1.00	10
SAP Developer	1.00	1.00	1.00	7
Sales	1.00	1.00	1.00	8
Testing	1.00	1.00	1.00	16
Web Designing	1.00	1.00	1.00	5
accuracy			0.99	193
macro avg	0.99	1.00	1.00	193
weighted avg	1.00	0.99	0.99	193

```
Fitting 3 folds for each of 6 candidates, totalling 18 fits
Best SVM Parameters: {'C': 1, 'kernel': 'linear'}
SVM Accuracy: 0.9948186528497409
```

	precision	recall	f1-score	support
Advocate	1.00	1.00	1.00	3
Arts	1.00	1.00	1.00	6
Automation Testing	1.00	1.00	1.00	5
Blockchain	1.00	1.00	1.00	7
Business Analyst	0.80	1.00	0.89	4
Civil Engineer	1.00	1.00	1.00	9
Data Science	1.00	1.00	1.00	5
Database	1.00	1.00	1.00	8
DevOps Engineer	1.00	0.93	0.96	14
DotNet Developer	1.00	1.00	1.00	5
ETL Developer	1.00	1.00	1.00	7
Electrical Engineering	1.00	1.00	1.00	6
HR	1.00	1.00	1.00	12
Hadoop	1.00	1.00	1.00	4
Health and fitness	1.00	1.00	1.00	7
Java Developer	1.00	1.00	1.00	15
Mechanical Engineer	1.00	1.00	1.00	8
Network Security Engineer	1.00	1.00	1.00	3
Operations Manager	1.00	1.00	1.00	12
PMO	1.00	1.00	1.00	7
Python Developer	1.00	1.00	1.00	10

SAP Developer	1.00	1.00	1.00	7
Sales	1.00	1.00	1.00	8
Testing	1.00	1.00	1.00	16
Web Designing	1.00	1.00	1.00	5
accuracy			0.99	193
macro avg	0.99	1.00	0.99	193
weighted avg	1.00	0.99	1.00	193

Naive Bayes Accuracy: 0.9896373056994818

	precision	recall	f1-score	support
Advocate	1.00	1.00	1.00	3
Arts	1.00	1.00	1.00	6
Automation Testing	1.00	1.00	1.00	5
Blockchain	1.00	1.00	1.00	7
Business Analyst	1.00	1.00	1.00	4
Civil Engineer	1.00	1.00	1.00	9
Data Science	1.00	1.00	1.00	5
Database	1.00	1.00	1.00	8
DevOps Engineer	1.00	0.93	0.96	14
DotNet Developer	1.00	1.00	1.00	5
ETL Developer	1.00	1.00	1.00	7
Electrical Engineering	1.00	1.00	1.00	6
HR	1.00	0.92	0.96	12
Hadoop	1.00	1.00	1.00	4
Health and fitness	1.00	1.00	1.00	7
Java Developer	0.94	1.00	0.97	15
Mechanical Engineer	1.00	1.00	1.00	8
Network Security Engineer	1.00	1.00	1.00	3
Operations Manager	1.00	1.00	1.00	12
PMO	0.88	1.00	0.93	7
Python Developer	1.00	1.00	1.00	10
SAP Developer	1.00	1.00	1.00	7
Sales	1.00	1.00	1.00	8
Testing	1.00	1.00	1.00	16
Web Designing	1.00	1.00	1.00	5
accuracy			0.99	193
macro avg	0.99	0.99	0.99	193
weighted avg	0.99	0.99	0.99	193

8 Deep Learning Model using TensorFlow/Keras

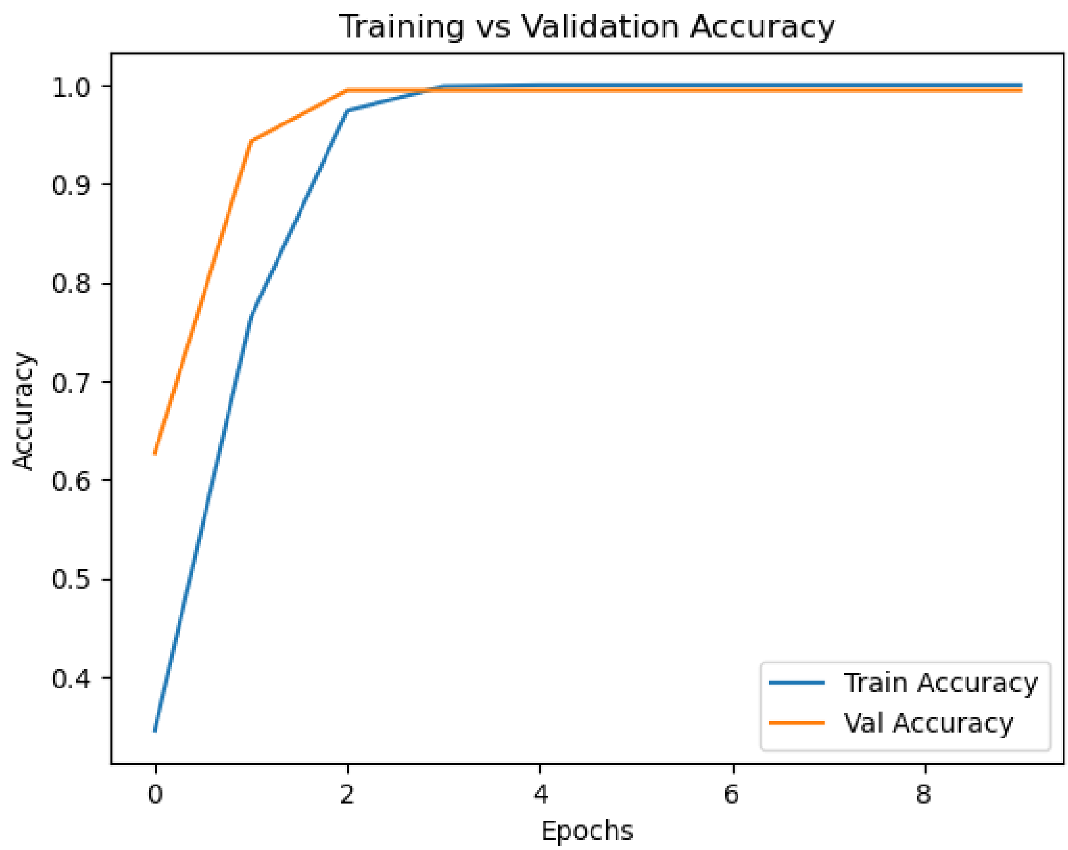
[17]:
```
import warnings
warnings.filterwarnings('ignore')
# Convert text data to dense format and labels to one-hot
X_dense = X.toarray()
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
y_categorical = to_categorical(y_encoded)

# Split data
X_train_dl, X_test_dl, y_train_dl, y_test_dl = train_test_split(X_dense,␣
↪y_categorical, test_size=0.2, random_state=42)

# Build the deep learning model
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(X_train_dl.shape[1],)))
model.add(Dropout(0.3))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(y_categorical.shape[1], activation='softmax'))

# Compile model
model.compile(loss='categorical_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])

# Train the model
history = model.fit(X_train_dl, y_train_dl, epochs=10, batch_size=32,␣
↪validation_data=(X_test_dl, y_test_dl))

# Evaluate the model
loss, accuracy = model.evaluate(X_test_dl, y_test_dl)
print(f"Deep Learning Model Accuracy: {accuracy:.4f}")

# Save the model
model.save("deep_learning_resume_classifier.h5")

# Save the label encoder for decoding predictions later
with open("label_encoder.pkl", "wb") as f:
    pickle.dump(label_encoder, f)

#Visualization
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title('Training vs Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
```

```
plt.legend()
plt.show()
```

```
Epoch 1/10
25/25            2s 29ms/step -
accuracy: 0.2634 - loss: 3.1152 - val_accuracy: 0.6269 - val_loss: 2.4483
Epoch 2/10
25/25            1s 22ms/step -
accuracy: 0.6928 - loss: 2.0260 - val_accuracy: 0.9430 - val_loss: 0.8868
Epoch 3/10
25/25            1s 22ms/step -
accuracy: 0.9520 - loss: 0.5839 - val_accuracy: 0.9948 - val_loss: 0.1754
Epoch 4/10
25/25            1s 23ms/step -
accuracy: 0.9979 - loss: 0.1125 - val_accuracy: 0.9948 - val_loss: 0.0554
Epoch 5/10
25/25            1s 22ms/step -
accuracy: 1.0000 - loss: 0.0363 - val_accuracy: 0.9948 - val_loss: 0.0302
Epoch 6/10
25/25            1s 24ms/step -
accuracy: 1.0000 - loss: 0.0190 - val_accuracy: 0.9948 - val_loss: 0.0258
Epoch 7/10
25/25            1s 24ms/step -
accuracy: 1.0000 - loss: 0.0137 - val_accuracy: 0.9948 - val_loss: 0.0175
Epoch 8/10
25/25            1s 22ms/step -
accuracy: 1.0000 - loss: 0.0087 - val_accuracy: 0.9948 - val_loss: 0.0189
Epoch 9/10
25/25            1s 21ms/step -
accuracy: 1.0000 - loss: 0.0070 - val_accuracy: 0.9948 - val_loss: 0.0185
Epoch 10/10
25/25            1s 22ms/step -
accuracy: 1.0000 - loss: 0.0058 - val_accuracy: 0.9948 - val_loss: 0.0149
7/7            0s 5ms/step -
accuracy: 0.9973 - loss: 0.0091
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

```
Deep Learning Model Accuracy: 0.9948
```



Note on Model Saving Format

While saving the deep learning model, Keras raises a warning that HDF5 format (`.h5`) is considered legacy. It recommends using the native Keras format instead (`.keras` extension).

However, `.h5` is still widely supported and perfectly fine for most real-world applications and deployments, especially with Flask-based setups. We're continuing with `.h5` for compatibility and simplicity.

If preferred, you can replace: `model.save("deep_learning_resume_classifier.h5")` with: `model.save("deep_learning_resume_classifier.keras")`

9 Deep Learning with LSTM (Sequential Modeling)

[20]:
```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout

# Prepare text for LSTM
```

```python
tokenizer = Tokenizer(num_words=10000, oov_token="<OOV>")
tokenizer.fit_on_texts(df['Cleaned_Resume'])

X_seq = tokenizer.texts_to_sequences(df['Cleaned_Resume'])
X_pad = pad_sequences(X_seq, maxlen=300)

# Encode labels again
y_lstm = to_categorical(label_encoder.transform(df['Category']))

X_train_lstm, X_test_lstm, y_train_lstm, y_test_lstm = train_test_split(X_pad,
 ↪y_lstm, test_size=0.2, random_state=42)

# LSTM Model
model_lstm = Sequential()
model_lstm.add(Embedding(input_dim=10000, output_dim=128, input_length=300))
model_lstm.add(LSTM(128, return_sequences=False))
model_lstm.add(Dropout(0.5))
model_lstm.add(Dense(64, activation='relu'))
model_lstm.add(Dense(y_lstm.shape[1], activation='softmax'))

model_lstm.compile(optimizer='adam', loss='categorical_crossentropy',
 ↪metrics=['accuracy'])

history_lstm = model_lstm.fit(X_train_lstm, y_train_lstm, epochs=5,
 ↪batch_size=32, validation_data=(X_test_lstm, y_test_lstm))

loss_lstm, acc_lstm = model_lstm.evaluate(X_test_lstm, y_test_lstm)
print(f"LSTM Model Accuracy: {acc_lstm:.4f}")

model_lstm.save("lstm_resume_classifier.h5")
```

```
Epoch 1/5
25/25              7s 186ms/step -
accuracy: 0.1228 - loss: 3.1966 - val_accuracy: 0.1451 - val_loss: 3.0383
Epoch 2/5
25/25              5s 183ms/step -
accuracy: 0.1995 - loss: 2.9340 - val_accuracy: 0.1606 - val_loss: 2.4912
Epoch 3/5
25/25              4s 175ms/step -
accuracy: 0.3174 - loss: 2.1789 - val_accuracy: 0.5285 - val_loss: 1.7723
Epoch 4/5
25/25              4s 169ms/step -
accuracy: 0.5958 - loss: 1.5631 - val_accuracy: 0.6736 - val_loss: 1.2248
Epoch 5/5
25/25              4s 170ms/step -
accuracy: 0.7250 - loss: 1.0891 - val_accuracy: 0.7409 - val_loss: 0.9937
7/7              0s 51ms/step -
```

```
accuracy: 0.7257 - loss: 1.0197
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

```
LSTM Model Accuracy: 0.7409
```

[55]:

```python
# Evaluate LSTM model
loss_lstm, acc_lstm = model_lstm.evaluate(X_test_lstm, y_test_lstm)
print(f"LSTM Model Accuracy: {acc_lstm:.4f}")

# Save the LSTM model
model_lstm.save("lstm_resume_classifier.h5")

# Save tokenizer
with open("tokenizer.pkl", "wb") as f:
    pickle.dump(tokenizer, f)
```

```
7/7            1s 62ms/step -
accuracy: 0.7257 - loss: 1.0197
```


```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```

```
LSTM Model Accuracy: 0.7409
```


10 Deployment using Flask

[32]:

```python
import os

# Create main project directory
os.makedirs("ResumeScreeningApp/templates", exist_ok=True)
os.makedirs("ResumeScreeningApp/static", exist_ok=True)
os.makedirs("ResumeScreeningApp/models", exist_ok=True)
```

[47]:

```python
# Save your model
with open("ResumeScreeningApp/models/random_forest_model.pkl", "wb") as f:
    pickle.dump(rf_model, f)

# Save TF-IDF vectorizer
with open("ResumeScreeningApp/models/tfidf_vectorizer.pkl", "wb") as f:
    pickle.dump(vectorizer, f)
```

```python
# Save label encoder
with open("ResumeScreeningApp/models/label_encoder.pkl", "wb") as f:
    pickle.dump(label_encoder, f)
```

[53]:
```python
# Create index.html inside templates folder
with open("ResumeScreeningApp/templates/index.html", "w") as f:
    f.write("""<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Resume Screening App</title>
</head>
<body>
    <h2>Resume Screening</h2>
    <form action="/predict" method="post">
        <textarea name="resume" rows="15" cols="100" placeholder="Paste resume␣
↪text here..."></textarea><br><br>
        <input type="submit" value="Predict Job Category">
    </form>
    {% if prediction_text %}
        <h3>{{ prediction_text }}</h3>
    {% endif %}
</body>
</html>""")
```

To Test the App:

Run this in terminal:

cd ResumeScreeningApp

flask run

Open browser at: http://127.0.0.1:5000

[ ]:
```python

```