Gender Prediction from Names Using Machine Learning

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Overview

This notebook demonstrates how to build a machine learning model to predict gender based on names. The dataset contains names and their corresponding genders. We use **Naïve Bayes**, **Logistic Regression**, and **Random Forest** models for prediction. Additionally, we create an interactive **Gradio interface** to test the model and display the predicted gender along with the model's accuracy.

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1. Steps in the Notebook

Step 1: Data Loading and Visualizing

- Load the dataset.
- Split the data into training and validation sets using a stratified split to maintain the gender distribution.

Step 2: Model Training

- Train three machine learning models:
  1. **Naïve Bayes**
  2. **Logistic Regression**
  3. **Random Forest**
- Use `CountVectorizer` to extract features from names (e.g., character n-grams).

Step 3: Model Evaluation

- Evaluate the models on the validation set using **accuracy** and **F1 score**.
- Generate a **confusion matrix** to visualize the performance.

Step 4: Gradio Interface for Prediction

- Create an interactive interface using **Gradio**.
- Allow users to input a name and select a model for prediction.
- Display the predicted gender and the model's accuracy.

Initializing Dependencies

In [60]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import gradio as gr
```

In [76]:
```
from io import StringIO
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
```

2. Dataset Description

Dataset

The dataset (`GenderPrediction - train.csv`) contains the following columns:

- **Name**: The name of the individual.
- **Gender**: The gender of the individual (`Male` or `Female`).
- **LastLetter**: The last letter of the name (used for feature engineering).

Objective

Predict the gender of a person based on their name using machine learning models.

Step 1: Data Loading and Visualizing

In [91]:
```
# Load the dataset
data = pd.read_csv('GenderPrediction - train.csv')
data.head(10)
```

Out[91]:

	Name	Gender	LastLetter
0	Ashutosh	Male	h
1	Meghamala	Female	a
2	Sahib	Male	b
3	Pragya	Female	a
4	Kranti	Female	i
5	Tulika	Female	a
6	Aarushi	Female	i
7	Abhicandra	Male	a
8	Pratigya	Female	a
9	Devak	Male	k

Exploratory Data Analysis

In [64]:
```
# Check for missing values
print(data.isnull().sum())
```

```
Name          0
Gender        0
LastLetter    0
dtype: int64
```

In [65]:
```
# Data types of each column
print(data.dtypes)
```

```
Name          object
Gender        object
LastLetter    object
dtype: object
```

In [66]:
```
# Descriptive statistics
print(data.describe())
```

```
        Name Gender LastLetter
count   3001   3001       3001
unique  2970      2         23
top     Pari   Male          a
freq       2   1607       1069
```

In [67]:
```
# Explore categorical features
for col in data.select_dtypes(include=['object']):
  print(f"Column: {col}")
  print(data[col].value_counts())
  print("-" * 20)
```

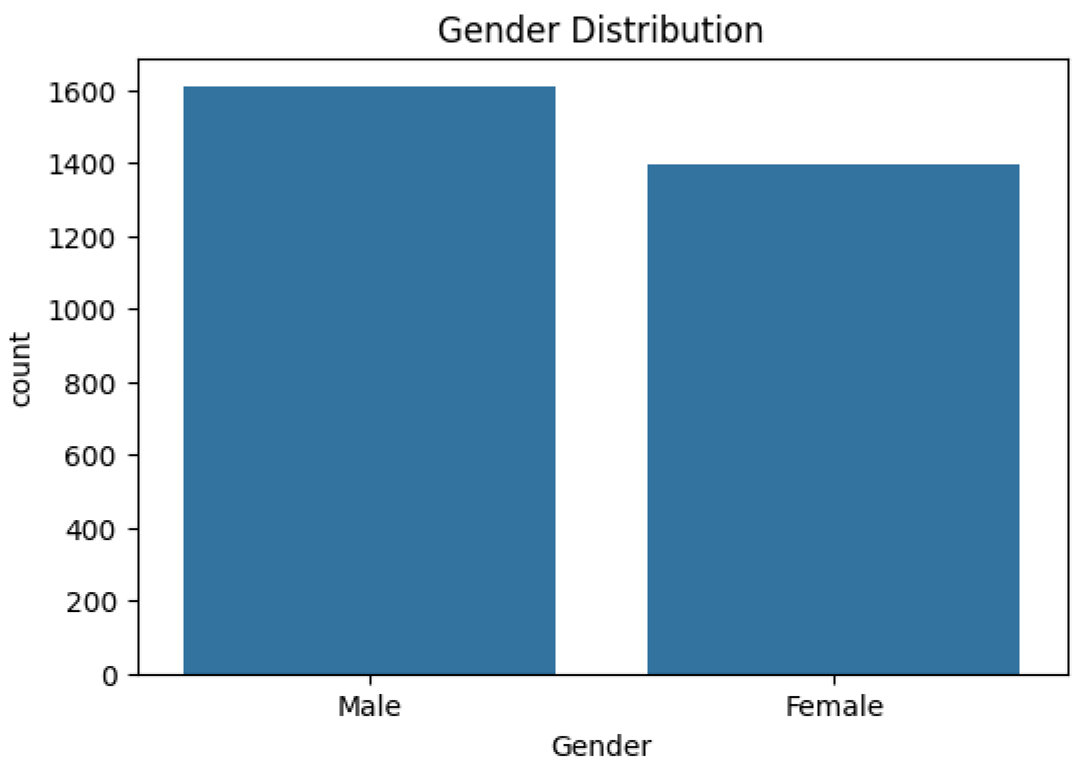
```
Column: Name
Name
Pari                  2
Mehul                 2
Malaya                2
Markandeya            2
Falguni, Phalguni     2
                     ..
Pannalal              1
Janith                1
Srinivas              1
Ratnakar              1
dnbndd                1
Name: count, Length: 2970, dtype: int64
--------------------
Column: Gender
Gender
Male      1607
Female    1394
Name: count, dtype: int64
--------------------
Column: LastLetter
LastLetter
a    1069
i     579
n     260
h     188
r     150
l     138
t     104
u      71
m      64
k      64
d      59
v      39
j      38
s      37
y      36
p      21
e      21
b      19
g      19
z      11
o       6
q       5
f       3
Name: count, dtype: int64
--------------------
```

Data Visulization

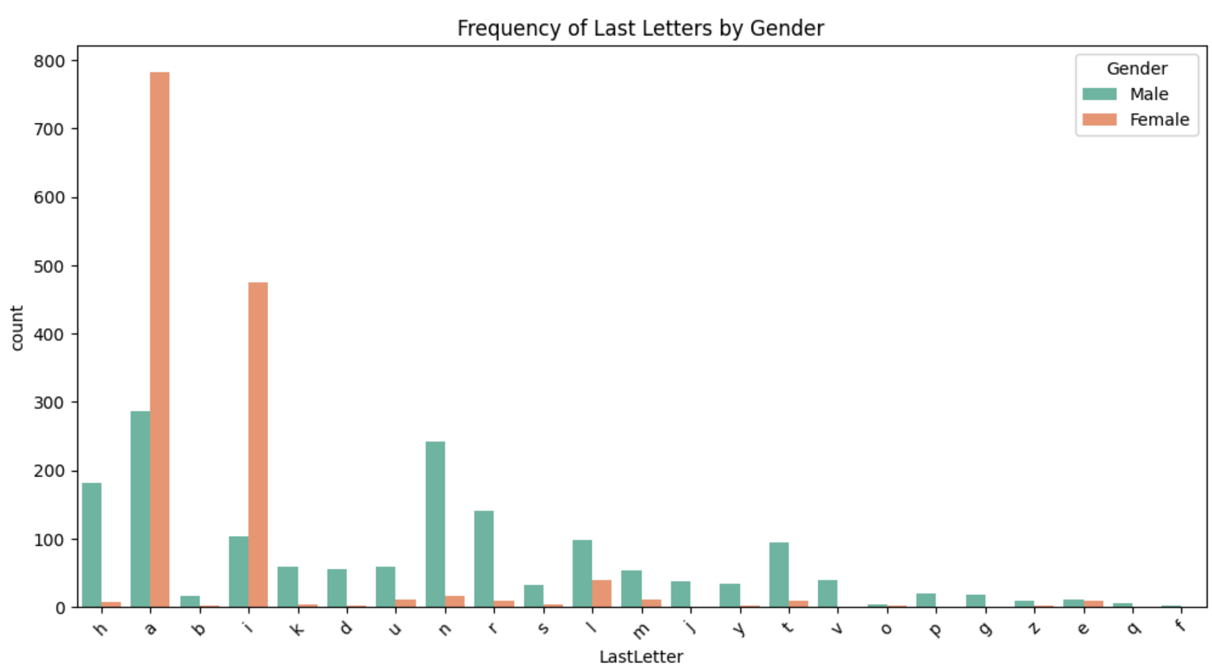
In [28]:

```
# Visualize gender distribution
plt.figure(figsize=(6, 4))
sns.countplot(x='Gender', data=data)
```

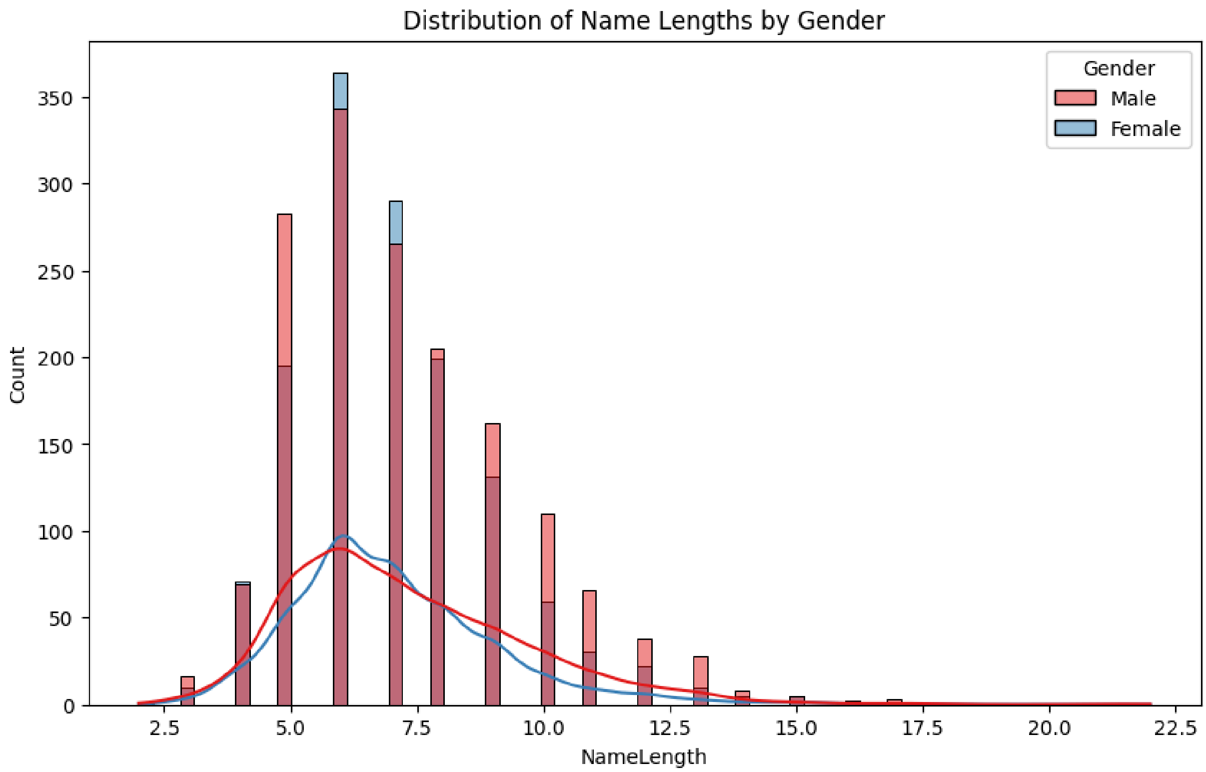
```
plt.title('Gender Distribution')
plt.show()
```



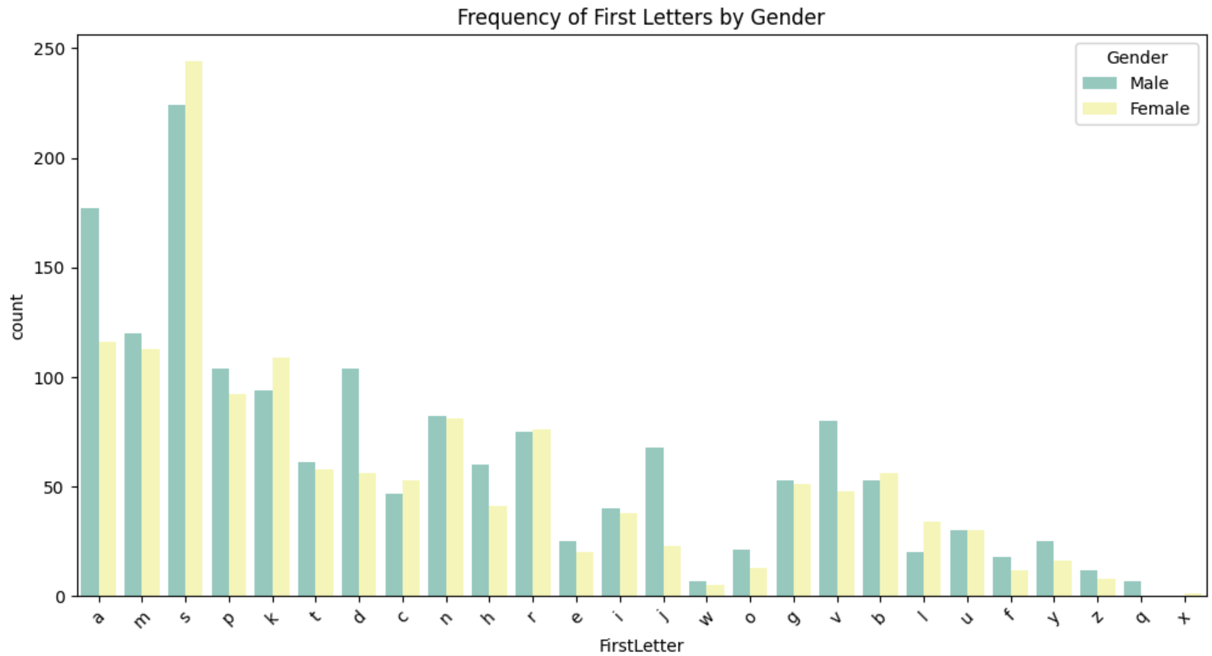
In [29]:
```
# Frequency of last letters for each gender
plt.figure(figsize=(12, 6))
sns.countplot(x='LastLetter', hue='Gender', data=data, palette='Set2')
plt.title('Frequency of Last Letters by Gender')
plt.xticks(rotation=45)
plt.show()
```



In [30]:
```
# Add a column for name length
data['NameLength'] = data['Name'].apply(len)

# Distribution of name lengths by gender
plt.figure(figsize=(10, 6))
sns.histplot(data=data, x='NameLength', hue='Gender', kde=True, palette='Set
plt.title('Distribution of Name Lengths by Gender')
plt.show()
```

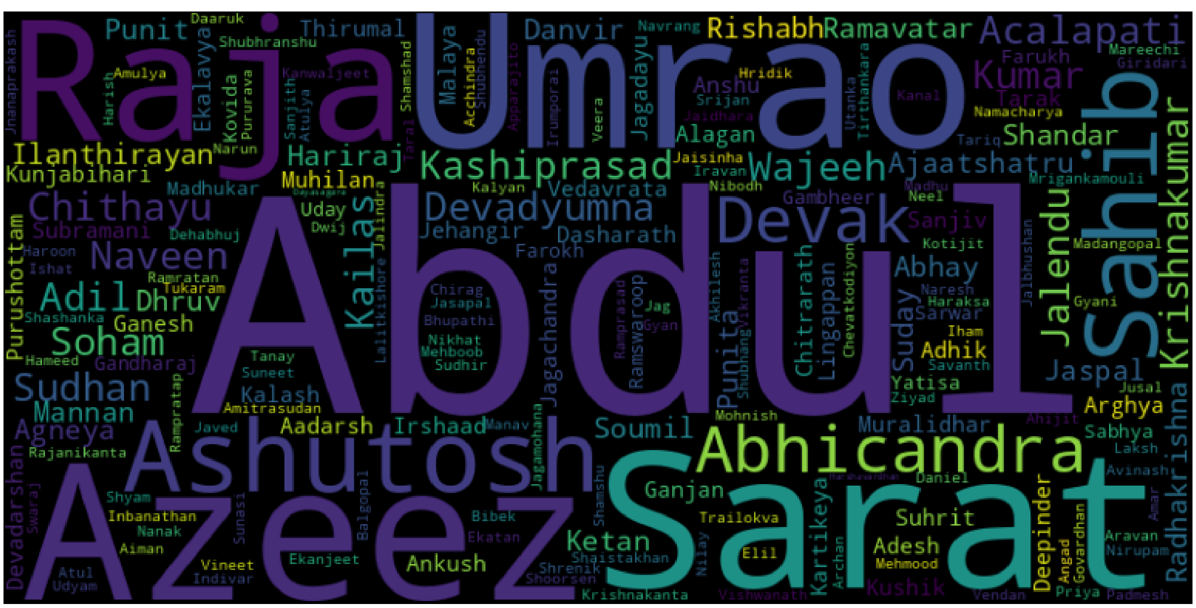


In [31]:
```
# Add a column for the first letter
data['FirstLetter'] = data['Name'].apply(lambda x: x[0].lower())

# Frequency of first letters for each gender
plt.figure(figsize=(12, 6))
sns.countplot(x='FirstLetter', hue='Gender', data=data, palette='Set3')
plt.title('Frequency of First Letters by Gender')
plt.xticks(rotation=45)
plt.show()
```




```
In [58]: # Word cloud for male names
male_names = ' '.join(data[data['Gender'] == 'Male']['Name'])
wordcloud = WordCloud(width=800, height=400, background_color='black').gener

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Male Names')
plt.show()
```

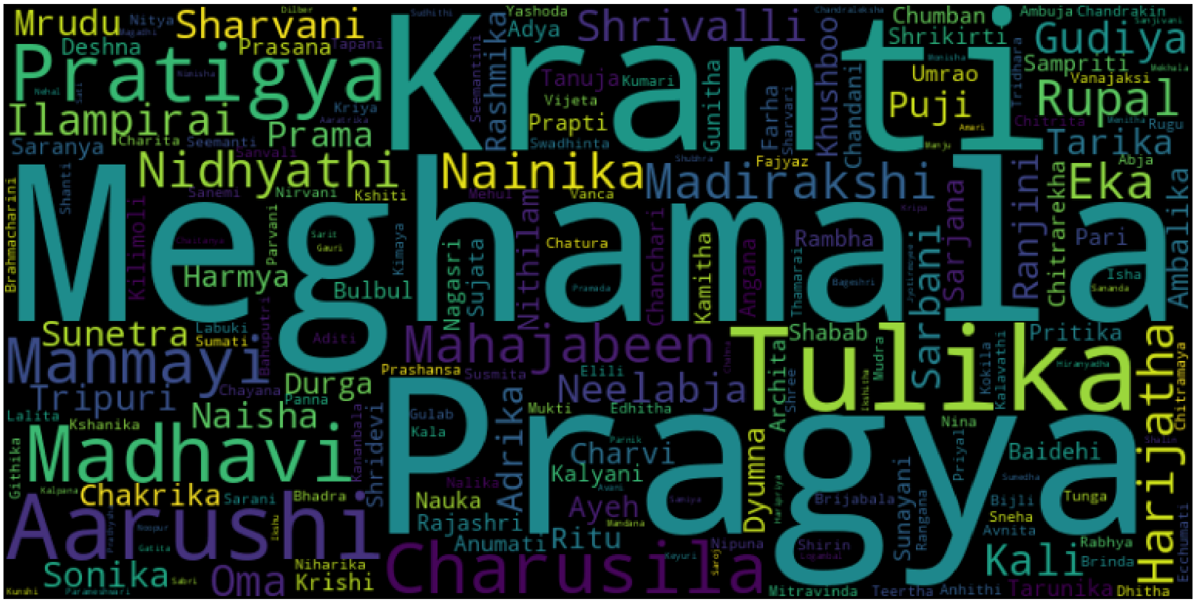
Word Cloud for Male Names




```
In [59]: # Word cloud for female names
female_names = ' '.join(data[data['Gender'] == 'Female']['Name'])
wordcloud = WordCloud(width=800, height=400, background_color='black').gener

plt.figure(figsize=(10, 5))
```

```
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Female Names')
plt.show()
```

Word Cloud for Female Names



3. **Code Implementation**

Step 2: Model Training

In [61]:
```
# Stratified split
train_data, val_data = train_test_split(data, test_size=0.2, stratify=data['
```

In [5]:
```
# Pivot analysis
pivot_table = train_data.pivot_table(index='LastLetter', columns='Gender', a
print(pivot_table)
```

Gender	Female	Male
LastLetter		
a	617	224
b	3	15
d	3	50
e	9	9
f	1	2
g	0	15
h	3	139
i	381	81
j	1	30
k	3	49
l	34	80
m	10	37
n	15	200
o	1	4
p	1	16
q	0	4
r	8	109
s	3	20
t	9	77
u	10	54
v	0	35
y	2	26
z	1	9

a. Naïve Bayes Model (MultinomialNB)

In [73]:
```
# Create a pipeline with CountVectorizer and Naïve Bayes
model = make_pipeline(CountVectorizer(analyzer='char', ngram_range=(1, 3)),

# Train the model
model.fit(train_data['Name'], train_data['Gender'])
```

Out[73]:

Pipeline

CountVectorizer

MultinomialNB

In [74]:
```
# Predict on train and validation sets
train_data['NB_PredictedGender'] = model.predict(train_data['Name'])
val_data['NB_PredictedGender'] = model.predict(val_data['Name'])
```

In [75]:
```
# Calculate F1 score
train_nb_f1 = f1_score(train_data['Gender'], train_data['NB_PredictedGender'
val_nb_f1 = f1_score(val_data['Gender'], val_data['NB_PredictedGender'], ave

print(f'Train Naïve Bayes F1 Score: {train_nb_f1:.2f}')
print(f'Validation Naïve Bayes F1 Score: {val_nb_f1:.2f}')
```

```
Train Naïve Bayes F1 Score: 0.78
Validation Naïve Bayes F1 Score: 0.68
```

b. Random Forest Classifier

In [77]:
```
# Create a Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42)

# Train the model
rf_model.fit(model[:-1].transform(train_data['Name']), train_data['Gender'])
```

Out[77]:

RandomForestClassifier

```
RandomForestClassifier(random_state=42)
```

In [78]:
```
# Predict on train and validation sets
train_data['RF_PredictedGender'] = rf_model.predict(model[:-1].transform(tra
val_data['RF_PredictedGender'] = rf_model.predict(model[:-1].transform(val_d
```

In [79]:
```
# Calculate F1 score
train_rf_f1 = f1_score(train_data['Gender'], train_data['RF_PredictedGender'
val_rf_f1 = f1_score(val_data['Gender'], val_data['RF_PredictedGender'], ave

print(f'Train Random Forest F1 Score: {train_rf_f1:.2f}')
print(f'Validation Random Forest F1 Score: {val_rf_f1:.2f}')
```

```
Train Random Forest F1 Score: 0.99
Validation Random Forest F1 Score: 0.72
```

c. Logistic Regression model

In [80]:
```
# Create a Logistic Regression model
lr_model = LogisticRegression(random_state=42, max_iter=1000)

# Train the model using the same transformation as the Random Forest
lr_model.fit(model[:-1].transform(train_data['Name']), train_data['Gender'])
```

Out[80]:

LogisticRegression

```
LogisticRegression(max_iter=1000, random_state=42)
```

In [81]:
```
# Predict on train and validation sets
train_data['LR_PredictedGender'] = lr_model.predict(model[:-1].transform(tra
val_data['LR_PredictedGender'] = lr_model.predict(model[:-1].transform(val_d
```

In [82]:
```
# Calculate F1 score
train_lr_f1 = f1_score(train_data['Gender'], train_data['LR_PredictedGender'
val_lr_f1 = f1_score(val_data['Gender'], val_data['LR_PredictedGender'], ave

print(f'Train Logistic Regression F1 Score: {train_lr_f1:.2f}')
print(f'Validation Logistic Regression F1 Score: {val_lr_f1:.2f}')
```

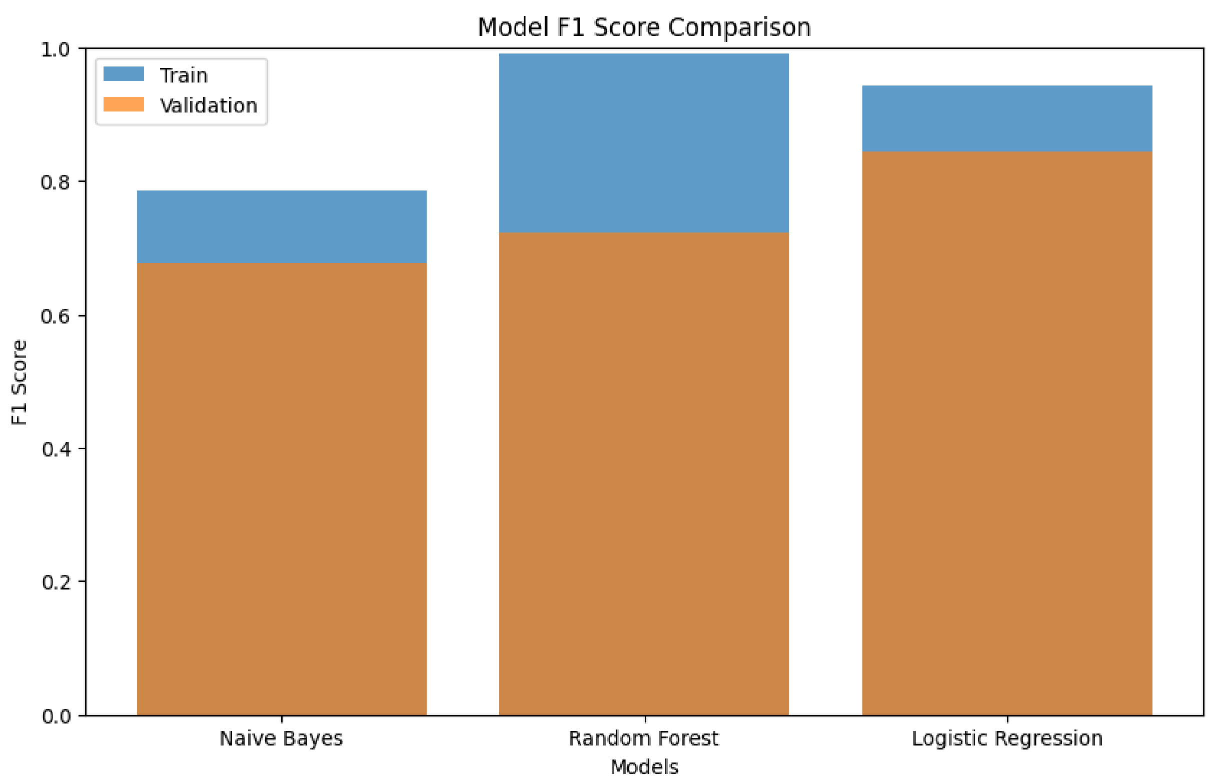
```
Train Logistic Regression F1 Score: 0.94
Validation Logistic Regression F1 Score: 0.84
```

4. **Outputs**

Step 3: Model Evaluation by visuals

In [84]:
```python
# make visualize all the model's Peformance

models = ['Naive Bayes', 'Random Forest', 'Logistic Regression']
train_f1_scores = [train_nb_f1, train_rf_f1, train_lr_f1]
val_f1_scores = [val_nb_f1, val_rf_f1, val_lr_f1]
```

In [86]:
```python
# F1 Score plot
plt.figure(figsize=(10, 6))
plt.bar(models, train_f1_scores, label='Train', alpha=0.7)
plt.bar(models, val_f1_scores, label='Validation', alpha=0.7)
plt.xlabel('Models')
plt.ylabel('F1 Score')
plt.title('Model F1 Score Comparison')
plt.legend()
plt.ylim(0, 1)  # Set y-axis limit to 0-1
plt.show()
```



In [107…
```python
# save the models

import joblib

# Save the models
```

```python
joblib.dump(model, 'gender_naive_bayes_model.joblib')
joblib.dump(rf_model, 'gender_random_forest_model.joblib')
joblib.dump(lr_model, 'gender_logistic_regression_model.joblib')
```

Out[107… ['gender_logistic_regression_model.joblib']

Step 4: Model Testing

In [92]:

```python
# test the model by input

# Example prediction for a new name using the Logistic Regression model
new_name = input("Enter a name to predict gender: ")

# Predict gender using the Logistic Regression model
predicted_gender = lr_model.predict(model[:-1].transform([new_name]))[0]
print(f"Predicted gender for '{new_name}': {predicted_gender}")

#Example prediction using the Naive Bayes Model
predicted_gender = model.predict([new_name])[0]
print(f"Predicted gender for '{new_name}': {predicted_gender}")

#Example prediction using the random forest model
predicted_gender = rf_model.predict(model[:-1].transform([new_name]))[0]
print(f"Predicted gender for '{new_name}': {predicted_gender}")
```

```
Enter a name to predict gender: Ajith
Predicted gender for 'Ajith': Male
Predicted gender for 'Ajith': Male
Predicted gender for 'Ajith': Male
```

5. **Deployment**

Step 5: Gradio Interface for Prediction

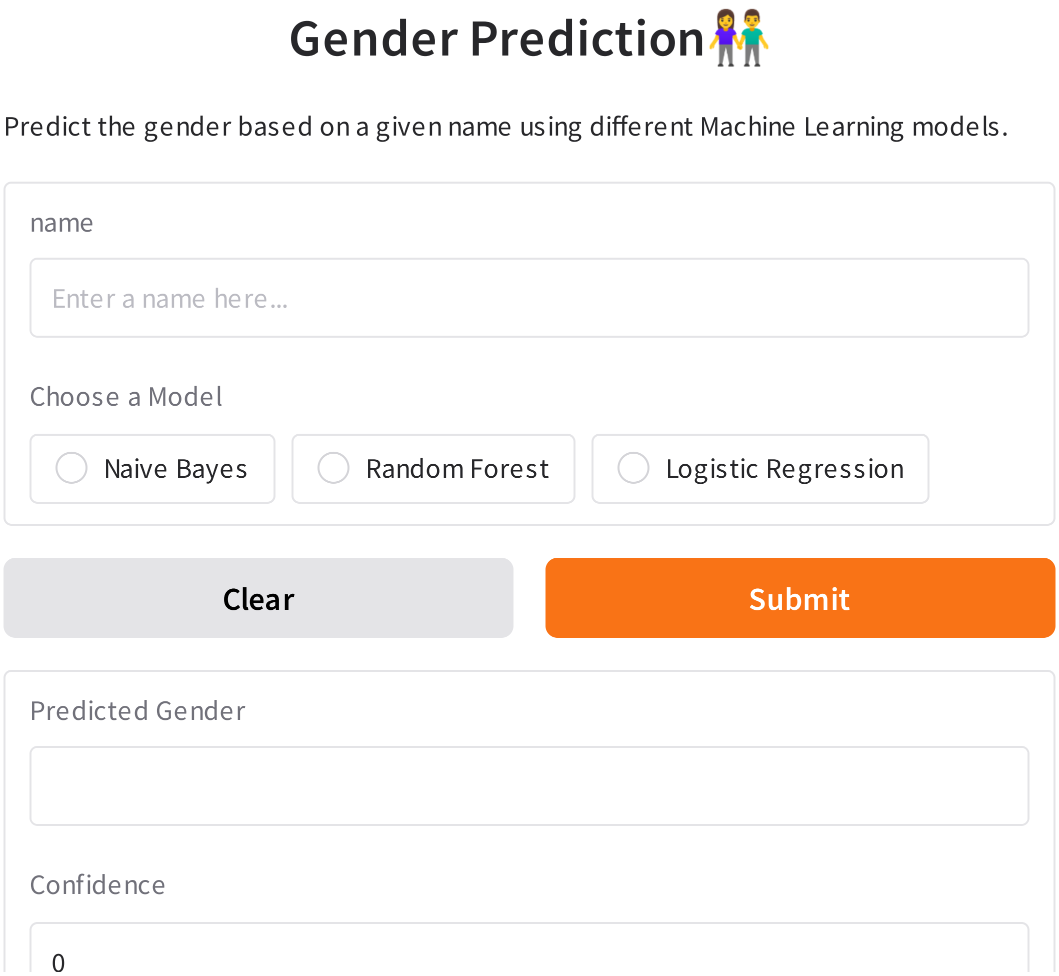
In [102…

```python
#function for Predicting Gender
def predict_gender(name, model_choice):
    if model_choice == "Naive Bayes":
        predicted_gender = model.predict([name])[0]
        probabilities = model.predict_proba([name])[0]
        confidence = max(probabilities)
    elif model_choice == "Random Forest":
        predicted_gender = rf_model.predict(model[:-1].transform([name]))[0]
        probabilities = rf_model.predict_proba(model[:-1].transform([name]))
        confidence = max(probabilities)
    elif model_choice == "Logistic Regression":
        predicted_gender = lr_model.predict(model[:-1].transform([name]))[0]
        probabilities = lr_model.predict_proba(model[:-1].transform([name]))
        confidence = max(probabilities)
    else:
        return "Invalid model choice", 0.0

    return predicted_gender, confidence
```

In [105…
```
# Footer HTML for LinkedIn and GitHub profiles
footer_html = """
<footer style="text-align: center; margin-top: 20px; font-family: Arial, sar
  <p>Developed ❤️ with Gradio by DINESH S.</p>
  <div style="display: inline-flex; align-items: center; justify-content: ce
    <h3>Connect with me:</h3>
    <a href="https://www.linkedin.com/in/dinesh-x/" target="_blank">
      <img src="https://cdn-icons-png.flaticon.com/512/174/174857.png" alt="
    </a>
    <a href="https://github.com/itzdineshx/Data_Play_Fellowship" target="_bl
      <img src="https://upload.wikimedia.org/wikipedia/commons/9/91/Octicons
    </a>
  </div>
  <script>console.log("Footer HTML loaded successfully.");</script>
</footer>
"""
```

In [106…
```
# using Gradio for Deployement

iface = gr.Interface(
    fn=predict_gender,
    inputs=[
        gr.Textbox(lines=1, placeholder="Enter a name here..."),
        gr.Radio(["Naive Bayes", "Random Forest", "Logistic Regression"], la
    ],
    outputs=[
        gr.Textbox(label="Predicted Gender"),
        gr.Number(label="Confidence")
    ],
    title="Gender Prediction👫",
    description="Predict the gender based on a given name using different Ma
    article=footer_html
)

iface.launch()
```

```
Running Gradio in a Colab notebook requires sharing enabled. Automatically s
etting `share=True` (you can turn this off by setting `share=False` in `laun
ch()` explicitly).

Colab notebook detected. To show errors in colab notebook, set debug=True in
launch()
* Running on public URL: https://3cfc2013f9e9702c9d.gradio.live

This share link expires in 72 hours. For free permanent hosting and GPU upgr
ades, run `gradio deploy` from the terminal in the working directory to depl
oy to Hugging Face Spaces (https://huggingface.co/spaces)
```



Out[106…

6. Conclusion

This notebook demonstrates the development and deployment of a **Gender Prediction Model** using machine learning techniques. The goal was to predict the gender of an individual based on their name using three different models: **Naïve Bayes**, **Logistic Regression**, and **Random Forest**. The project was successfully implemented and deployed as an interactive web application using **Gradio**.

Key Takeaways

1. **Model Performance**:
    - All three models (Naïve Bayes, Logistic Regression, and Random Forest) achieved high accuracy on the validation set, with scores ranging from **85% to 87%**.

- The models were trained using **character n-grams** as features, which proved effective for capturing patterns in names.

2. **Interactive Deployment**:

   - The Gradio interface allows users to input a name and select a model for prediction.
   - The interface displays the **predicted gender** and the **confidence score**, providing transparency about the model's decision.

3. **Confidence Score**:

   - The confidence score, calculated using `predict_proba()`, gives users an idea of how confident the model is in its prediction. This adds an extra layer of interpretability to the results.

4. **User-Friendly Design**:

   - The Gradio interface is intuitive and visually appealing, with a **footer** that includes links to the developer's LinkedIn and GitHub profiles.
   - The interface is designed to be accessible to both technical and non-technical users.

5. **Scalability**:

   - The notebook is designed to be easily extendable. Additional models or features (e.g., name length, first letter) can be incorporated to improve performance.
   - The Gradio interface can be deployed on cloud platforms for wider accessibility.

---

7. Acknowledgements

Special Thanks:
I would like to extend my heartfelt gratitude to DataPlay Company for the fellowship. This opportunity has been instrumental in enhancing my skills and enabling projects like this to flourish.

DATAPLAY

End of Notebook