Pipeline in Jupyter Notebook

In [1]:

```
import os
import time

import torch
import torch.optim as optim
from torch.utils.data import DataLoader, random_split
from transformers import BertTokenizer
import seaborn as sns
import matplotlib.pyplot as plt

from src.data_preprocessing import load_data, preprocess_data, save_processe
from src.dataset import ContrastiveTextDataset, SupervisedTextDataset
from src.contrastive_learning import contrastive_pretrain
from src.evaluation import evaluate_classifier
from src.model import BertContrastiveModel
from src.supervised_fine_tune import fine_tune_supervised
```

```
/Users/ndminh/Minh/USA/University/University of Houston/Study/MSCS/Spring 20
25/COSC 6342/Project/gender-classification/venv/lib/python3.13/site-package
s/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter a
nd ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.
html
  from .autonotebook import tqdm as notebook_tqdm
[nltk_data] Downloading package punkt_tab to venv/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package stopwords to venv/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to venv/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to venv/nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
```

Preprocess the data

In [3]:

```
# Load and preprocess data
raw_data_path = "data/raw/gender-classification.csv"
processed_data_path = "data/processed"
processed_data_filename = "processed_data.csv"
text_column = "text"
label_column = "gender"

# Load raw data (csv file)
raw_data = load_data(raw_data_path)

# Preprocess data
preprocessed_data = preprocess_data(raw_data, text_column, label_column)

# Save preprocessed data to a csv file
save_processed_data(preprocessed_data, processed_data_path, processed_data_f
```

```
Data loaded successfully from: data/raw/gender-classification.csv
Data preprocessing completed successfully!
Processed data saved at: data/processed/processed_data.csv
```

In [4]:
```
# Load preprocessed data
data_df = load_data(f"{processed_data_path}/{processed_data_filename}")
```

```
Data loaded successfully from: data/processed/processed_data.csv
```

In [5]:
```
data_df.head()
```

Out[5]:

	text	gender
0	long time see like always rewriting scratch co...	0
1	guest demo eric iversons itty bitty search feb...	0
2	moved cheese world developing areas create dif...	0
3	yesterday attended biweekly meeting informal u...	0
4	liam nothing like natalie natalie never went d...	1

In [6]:
```
data_df.info()
data_df.describe()
data_df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3226 entries, 0 to 3225
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   text    3226 non-null   object
 1   gender  3226 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 50.5+ KB
```

Out[6]:
```
text      0
gender    0
dtype: int64
```

Contrastive Learning

Pre-train the model to learn the representation of the data in order to distinguish between similar and dissimilar data points.

In [7]:
```
# Texts will be used for contrastive learning
texts = data_df["text"].tolist()

print("Data loaded and preprocessed.")
print(f"Number of samples: {len(texts)}")
```

```
Data loaded and preprocessed.
Number of samples: 3226
```

In [8]:
```
# Initialize BERT tokenizer
```

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

In [9]:
```
# Create a custom dataset for contrastive learning
# This will perform data augmentation on the input text samples
# and prepare them for training

contrastive_dataset = ContrastiveTextDataset(
    texts, tokenizer, max_length=128, augment=True
)

contrastive_loader = DataLoader(contrastive_dataset, batch_size=8, shuffle=T

print("Contrastive dataset created (with data augmentation).")
```

```
Contrastive dataset created (with data augmentation).
```

In [10]:
```
# Initialize our model: BERT encoder with projection and classifier heads
model = BertContrastiveModel(proj_dim=64, num_labels=2, dropout_prob=0.3)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

print("Model initialized and moved to device.")
```

```
Model initialized and moved to device.
```

In [10]:
```
##################################
# CONTRASTIVE PRE-TRAINING PHASE
##################################


# Initialize the adam optimizer
optimizer_ctr = optim.Adam(model.parameters(), lr=2e-5, weight_decay=1e-4)

# Run contrastive pre-training
contrastive_pretrain(
    model,
    contrastive_loader,
    optimizer_ctr,
    device,
    num_epochs=5,
    temperature=0.5,
)

print("Contrastive pre-training complete. Model saved.")
```

```
Contrastive Pre-training Epoch [1/5] Loss: 1.5371
Contrastive Pre-training Epoch [2/5] Loss: 1.3300
Contrastive Pre-training Epoch [3/5] Loss: 1.2844
Contrastive Pre-training Epoch [4/5] Loss: 1.2617
Contrastive Pre-training Epoch [5/5] Loss: 1.2506
Model saved at models/bert_contrastive_pretrained.pth
Contrastive pre-training complete.
Contrastive pre-training complete. Model saved.
```

Supervised Fine-tuning

Fine-tune our pre-trained model on a classification task using labeled data.

In [11]:
```
# For this phase, we will also need the labels from the dataset

# texts = data_df["text"].tolist()
labels = data_df["gender"].tolist()

print("Data loaded and preprocessed.")
print(f"Number of samples: {len(texts)}")
print(f"Number of labels: {len(labels)}")
```

```
Data loaded and preprocessed.
Number of samples: 3226
Number of labels: 3226
```

In [12]:
```
# Create a custom dataset for supervised training
# This will not perform data augmentation on the input text samples
supervised_dataset = SupervisedTextDataset(
    texts, labels, tokenizer, max_length=128, augment=False
)

# Split data: 20% as test; from training, 20% as validation
total_len = len(supervised_dataset)
test_len = int(0.2 * total_len)
remaining = total_len - test_len
val_len = int(0.2 * remaining)
train_len = remaining - val_len

train_dataset, val_dataset, test_dataset = random_split(
    supervised_dataset, [train_len, val_len, test_len]
)

# Create data loaders for training, validation, and testing
batch_size = 16
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

print("Data loaded and split into train, validation, and test sets.")
```

```
Data loaded and split into train, validation, and test sets.
```

NOTE: This is important to cool down the machine a bit before running the supervised fine-tuning. After the contrastive learning, the machine will need to "take some rest" before running the next heavy task.

Just like a human brain, the machine needs to "rest" before running the next heavy task. It can help in a better performant and more accurate result.

In [13]:
```
# Let computer cool down in 5 minutes with no activity
print("Cooling down for 5 minutes...")
time.sleep(300)
print("Cool down complete. Resuming...")
```

```
Cooling down for 5 minutes...
Cool down complete. Resuming...
```

In [13]:
```
# Initialize our BertContrastiveModel
model = BertContrastiveModel(proj_dim=64, num_labels=2, dropout_prob=0.3)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

print("Model initialized and moved to device.")

# Load pre-trained contrastive model weights
pre_trained_path = os.path.join("models", "bert_contrastive_pretrained.pth")

# Check if the pre-trained model weights exist
if not os.path.exists(pre_trained_path):
    raise FileNotFoundError(
        f"Pre-trained model weights not found at {pre_trained_path}. Please
    )

model.load_state_dict(torch.load(pre_trained_path))

print("Loaded pre-trained contrastive model weights.")
```

```
Model initialized and moved to device.
Loaded pre-trained contrastive model weights.
```

In [39]:
```
################################
# SUPERVISED FINE-TUNING PHASE
################################



# Initialize the adam optimizer
optimizer_ft = optim.Adam(model.parameters(), lr=2e-5, weight_decay=1e-4)

# Perform model fine-tuning on labeled dataset
history, best_val_acc = fine_tune_supervised(
    model, train_loader, val_loader, optimizer_ft, device, num_epochs=20, pa
)

print(f"Best validation accuracy: {best_val_acc:.4f}")
print("Supervised fine-tuning complete. Model saved.")
```

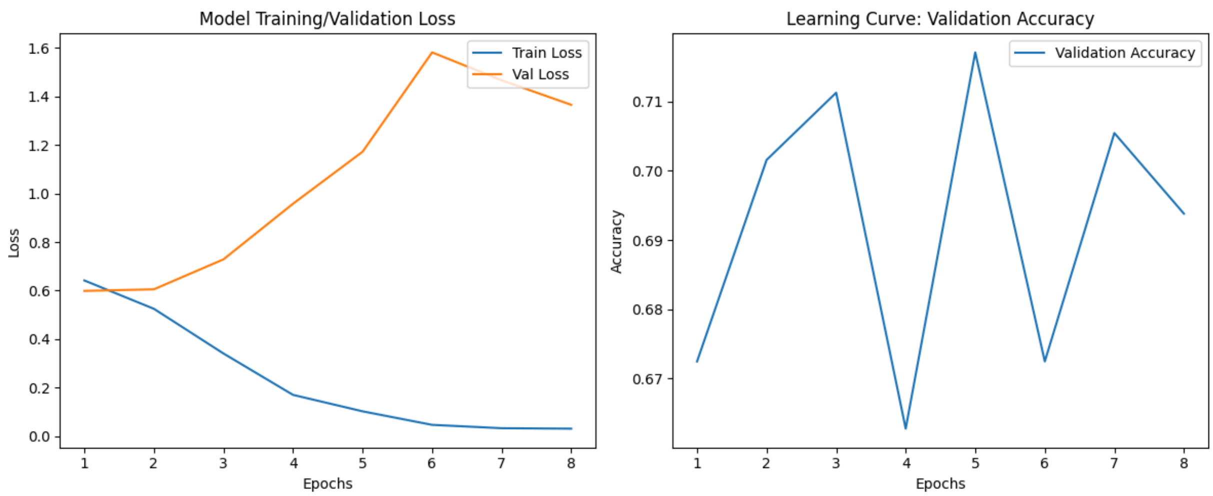
```
Epoch [1/20] - Train Loss: 0.6499, Val Loss: 0.6091, Val Acc: 0.7016
Best validation accuracy updated: 0.7016
Best supervised model updated and saved at models/best_bert_supervised.pth
Epoch [2/20] - Train Loss: 0.5849, Val Loss: 0.5652, Val Acc: 0.7112
Best validation accuracy updated: 0.7112
Best supervised model updated and saved at models/best_bert_supervised.pth
Epoch [3/20] - Train Loss: 0.4856, Val Loss: 0.5321, Val Acc: 0.7558
Best validation accuracy updated: 0.7558
Best supervised model updated and saved at models/best_bert_supervised.pth
Epoch [4/20] - Train Loss: 0.3015, Val Loss: 0.6531, Val Acc: 0.7229
Epoch [5/20] - Train Loss: 0.1285, Val Loss: 0.9160, Val Acc: 0.7054
Epoch [6/20] - Train Loss: 0.0550, Val Loss: 1.1800, Val Acc: 0.7112
Early stopping triggered. No improvement for 3 epochs.
Supervised fine-tuning complete.
Best validation accuracy: 0.7558
Supervised fine-tuning complete. Model saved.
```

In [14]:

```
####################################
# Plot supervised learning curves
####################################
def plot_learning_curves(history):
    epochs = range(1, len(history["train_loss"]) + 1)

    plt.figure(figsize=(12, 5))

    # Plot Loss
    plt.subplot(1, 2, 1)
    plt.plot(epochs, history["train_loss"], label="Train Loss")
    plt.plot(epochs, history["val_loss"], label="Validation Loss")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend(["Train Loss", "Val Loss"], loc="upper right")
    plt.title("Model Training/Validation Loss")

    # Plot Accuracy
    plt.subplot(1, 2, 2)
    plt.plot(epochs, history["val_accuracy"], label="Validation Accuracy")
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.title("Learning Curve: Validation Accuracy")

    plt.tight_layout()
    plt.show()
```

In [28]:

```
plot_learning_curves(history)
```



NOTE: This is important to cool down the machine again a bit before running the evaluation. After the contrastive learning and supervised fine-tuning, the machine is probably very "tired" and will need to "take some rest" before running the evaluation. It can help in a better and more accurate evaluation.

In [18]:
```
# Let computer cool down in 5 minutes with no activity
print("Cooling down for 5 minutes...")
time.sleep(300)
print("Cool down complete. Resuming...")
```

```
Cooling down for 5 minutes...
Cool down complete. Resuming...
```

Evaluation

Evaluate the model on a train/validation/test set to measure its performance.

In [20]:
```
# Initialize our BertContrastiveModel
model = BertContrastiveModel(proj_dim=64, num_labels=2, dropout_prob=0.3)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

print("Model initialized and moved to device.")
```

```
Model initialized and moved to device.
```

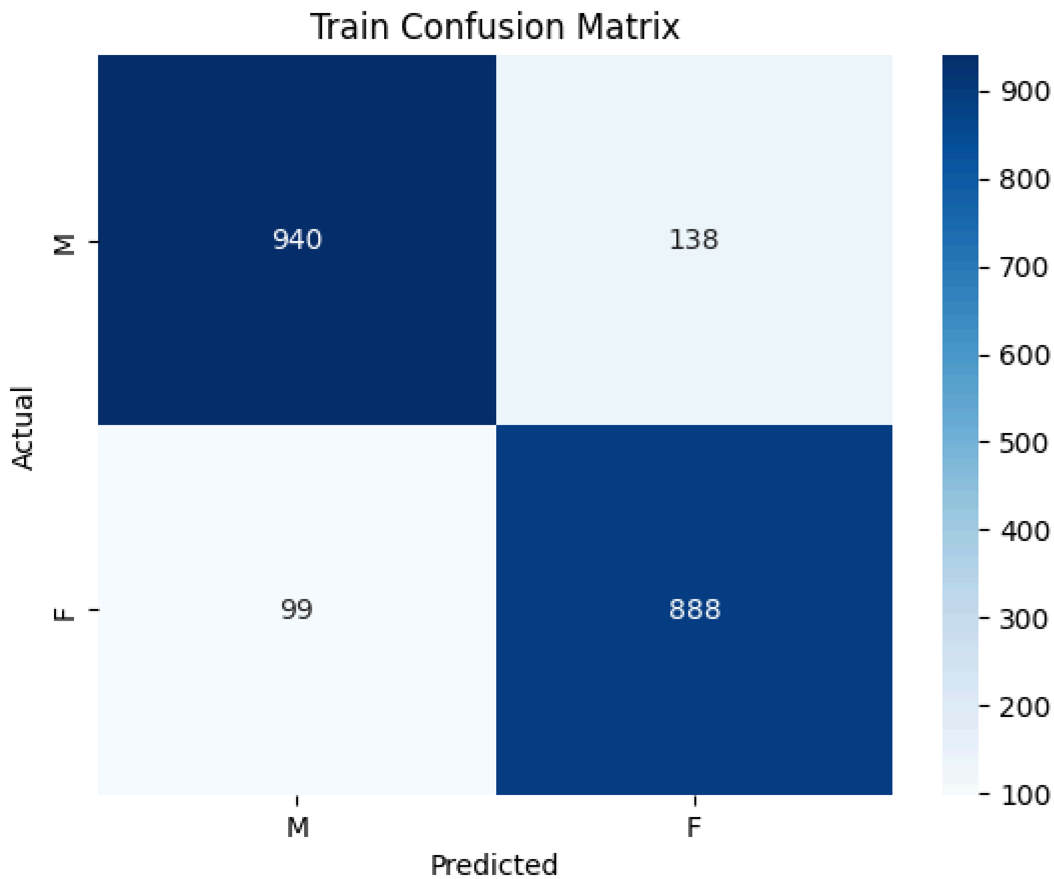
In [ ]:
```
# Load the supervised model weights
supervised_model_path = os.path.join("models", "best_bert_supervised.pth")
# Check if the supervised model weights exist
if not os.path.exists(supervised_model_path):
    raise FileNotFoundError(
        f"Supervised model weights not found at {supervised_model_path}. Ple
    )

model.load_state_dict(torch.load(supervised_model_path))

print("Loaded best supervised model weights.")
```

```
Loaded best supervised model weights.
```

In [22]:
```
def print_eval_results(results):
    """Prints the evaluation results.

    Args:
        results (dict): A dictionary containing evaluation metrics including
            loss, accuracy, f1 score, confusion matrix, and classification r
    """
    print(f"Loss: {results['loss']:.4f}")
    print(f"Accuracy: {results['accuracy']:.4f}")
    print(f"F1 Score: {results['f1']:.4f}")
    print("Confusion Matrix:")
    print(results["confusion_matrix"])
    print("Classification Report:")
    print(results["report"])
    print("=" * 30)
```

In [23]:
```
########################################
# Evaluate the model on the all 3 sets
#######################################

print("Evaluating on train set:")
train_eval = evaluate_classifier(model, train_loader, device)
print(f"Loss: {train_eval['loss']:.4f}")
print(f"Accuracy: {train_eval['accuracy']:.4f}")
print(f"F1 Score: {train_eval['f1']:.4f}")
print("Classification Report:")
print(train_eval["report"])

sns.heatmap(train_eval["confusion_matrix"], annot=True, fmt="d", cmap='Blues
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Train Confusion Matrix")
plt.show()

print("=" * 30)
```

```
Evaluating on train set:
Loss: 0.4395
Accuracy: 0.8852
F1 Score: 0.8853
Classification Report:
              precision    recall  f1-score   support

           M       0.90      0.87      0.89      1078
           F       0.87      0.90      0.88       987

    accuracy                           0.89      2065
   macro avg       0.89      0.89      0.89      2065
weighted avg       0.89      0.89      0.89      2065
```

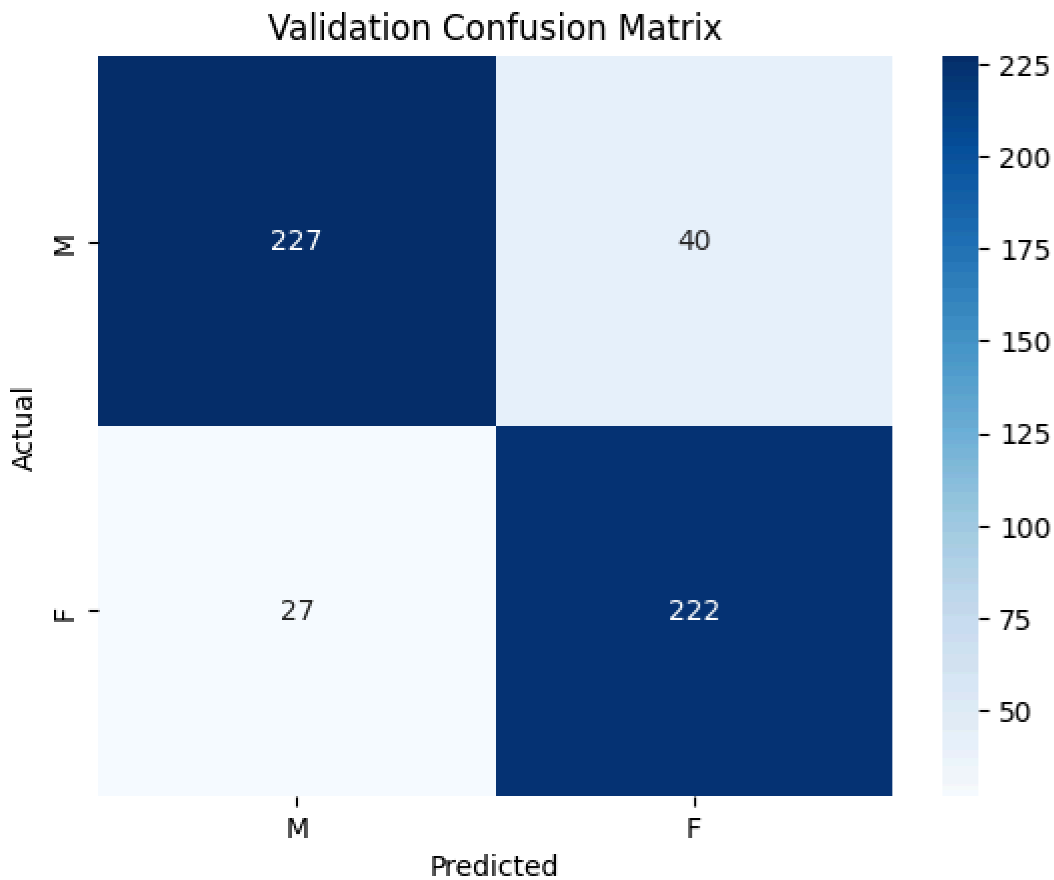


==============================

In [24]:

```
print("Evaluating on validation set:")
val_eval = evaluate_classifier(model, val_loader, device)
print(f"Loss: {val_eval['loss']:.4f}")
print(f"Accuracy: {val_eval['accuracy']:.4f}")
print(f"F1 Score: {val_eval['f1']:.4f}")
print("Classification Report:")
print(val_eval["report"])

sns.heatmap(val_eval["confusion_matrix"], annot=True, fmt="d", cmap='Blues',
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Validation Confusion Matrix")
plt.show()
```

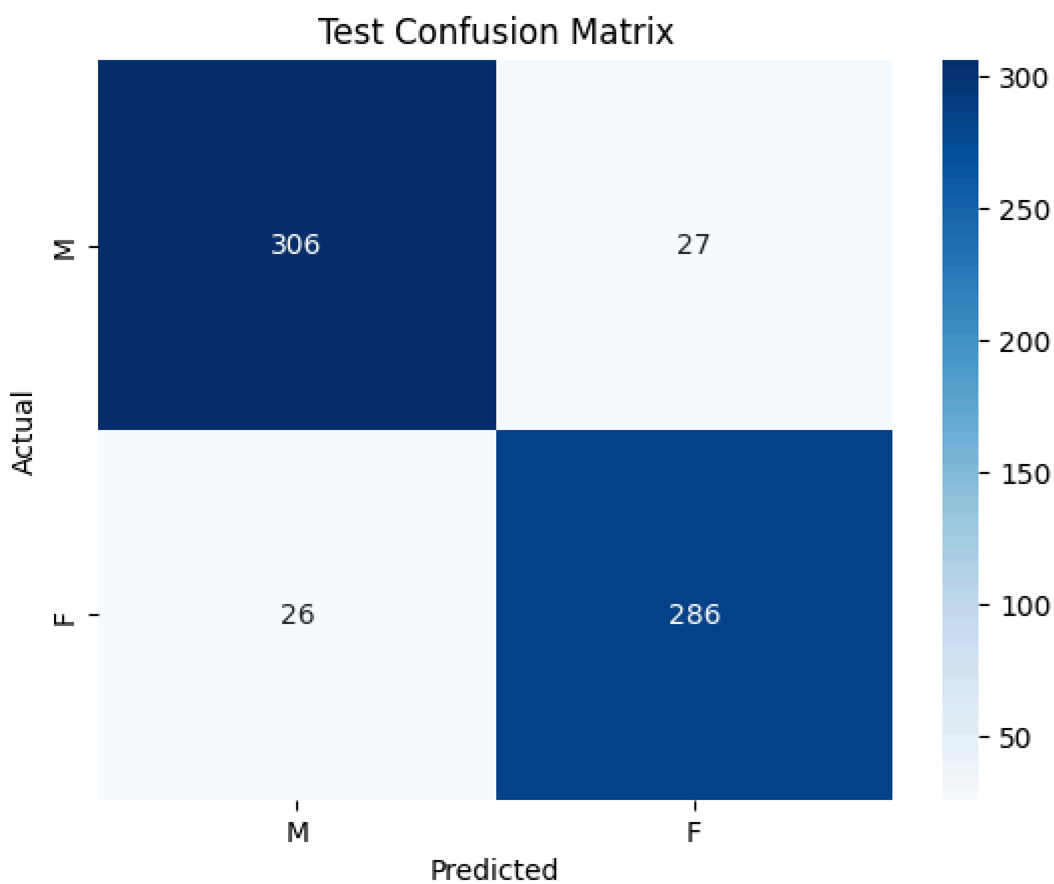
```
Evaluating on validation set:
Loss: 0.4450
Accuracy: 0.8702
F1 Score: 0.8702
Classification Report:
              precision    recall  f1-score   support

           M       0.89      0.85      0.87       267
           F       0.85      0.89      0.87       249

    accuracy                           0.87       516
   macro avg       0.87      0.87      0.87       516
weighted avg       0.87      0.87      0.87       516
```



In [25]:
```
print("Evaluating on test set:")
test_eval = evaluate_classifier(model, test_loader, device)
print(f"Loss: {test_eval['loss']:.4f}")
print(f"Accuracy: {test_eval['accuracy']:.4f}")
print(f"F1 Score: {test_eval['f1']:.4f}")
print("Classification Report:")
print(test_eval["report"])

sns.heatmap(test_eval["confusion_matrix"], annot=True, fmt="d", cmap='Blues'
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Test Confusion Matrix")
plt.show()
```

```python
print("=" * 30)
print("Evaluation complete.")
```

```
Evaluating on test set:
Loss: 0.3402
Accuracy: 0.9178
F1 Score: 0.9178
Classification Report:
              precision    recall  f1-score   support

           M       0.92      0.92      0.92       333
           F       0.91      0.92      0.92       312

    accuracy                           0.92       645
   macro avg       0.92      0.92      0.92       645
weighted avg       0.92      0.92      0.92       645
```




```
==============================
Evaluation complete.
```