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 sklearn.model_selection import train_test_split

from src.data_preprocessing import (
    load_data,
    preprocess_data,
    preprocess_blog_data,
    save_processed_data,
)
from src.dataset import SupervisedTextDataset, SupervisedContrastiveTextData
from src.contrastive_learning import supervised_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!
```

In [2]:

```
# Start the timer
start_time = time.time()
```

In [3]:

```
if torch.backends.mps.is_available():
    device = torch.device("mps")
elif torch.cuda.is_available():
    device = torch.device("cuda")
else:
    device = torch.device("cpu")
print(f"Using device: {device}")
```

```
Using device: mps
```

Preprocess the data

In [4]:
```
# 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"
```

In [5]:
```
# Load and preprocess external data (blogs data)
external_data_path = "data/raw/blogtext.csv"
processed_external_data_filename = "processed_blog_data.csv"
external_text_column = "text"
external_label_column = "gender"
```

In [6]:
```
# # 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
```

In [7]:
```
# Load blogtext data
# raw_external_data = load_data(external_data_path)
```

In [8]:
```
# Preprocess blogtext data
# preprocessed_external_data = preprocess_blog_data(
#     raw_external_data, external_text_column, external_label_column
# )

# # Save preprocessed blogtext data to a csv file
# save_processed_data(
#     preprocessed_external_data, processed_data_path, processed_external_da
# )
```

In [9]:
```
# Load preprocessed data
data_df = load_data(f"{processed_data_path}/{processed_data_filename}")
```

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

In [10]:
```
data_df.head()
```

Out[10]:

	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 [11]:

```
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[11]:

```
text      0
gender    0
dtype: int64
```

In [12]:

```
# Load processed blogtext data
blog_data_df = load_data(
    f"{processed_data_path}/{processed_external_data_filename}"
)
```

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

In [13]:

```
blog_data_df.head()
```

Out[13]:

	text	gender
0	info found 100 pages 45 mb pdf files wait unti...	0
1	team members drewes van der laag urllink mail ...	0
2	het kader van kernfusie op aarde maak je eigen...	0
3	testing testing	0
4	thanks yahoos toolbar capture urls popupswhich...	0

In [14]:

```
blog_data_df.info()
blog_data_df.describe()
blog_data_df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 611652 entries, 0 to 611651
Data columns (total 2 columns):
 #   Column  Non-Null Count   Dtype 
---  ------  --------------   ----- 
 0   text    611184 non-null  object
 1   gender  611652 non-null  int64 
dtypes: int64(1), object(1)
memory usage: 9.3+ MB
```

Out[14]:
```
text      468
gender      0
dtype: int64
```

In [15]:
```python
blog_data_df.dropna(subset=[external_text_column], inplace=True)
blog_data_df.isna().sum()
```

Out[15]:
```
text      0
gender    0
dtype: int64
```

In [16]:
```python
print(len(blog_data_df))
```

```
611184
```

Data Splitting

In [17]:
```python
# Texts will be used for contrastive learning
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
```

Contrastive Learning

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

In [18]:
```python
# Initialize BERT tokenizer
tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
```

In [19]:
```python
# Extract texts and labels for supervised contrastive learning pre-training
texts_ctr = blog_data_df["text"].tolist()
labels_ctr = blog_data_df["gender"].tolist()

print("Blog data (external) loaded and preprocessed for contrastive learning
print(f"Number of samples for contrastive learning: {len(texts_ctr)}")
print(f"Number of labels for contrastive learning: {len(labels_ctr)}")
```

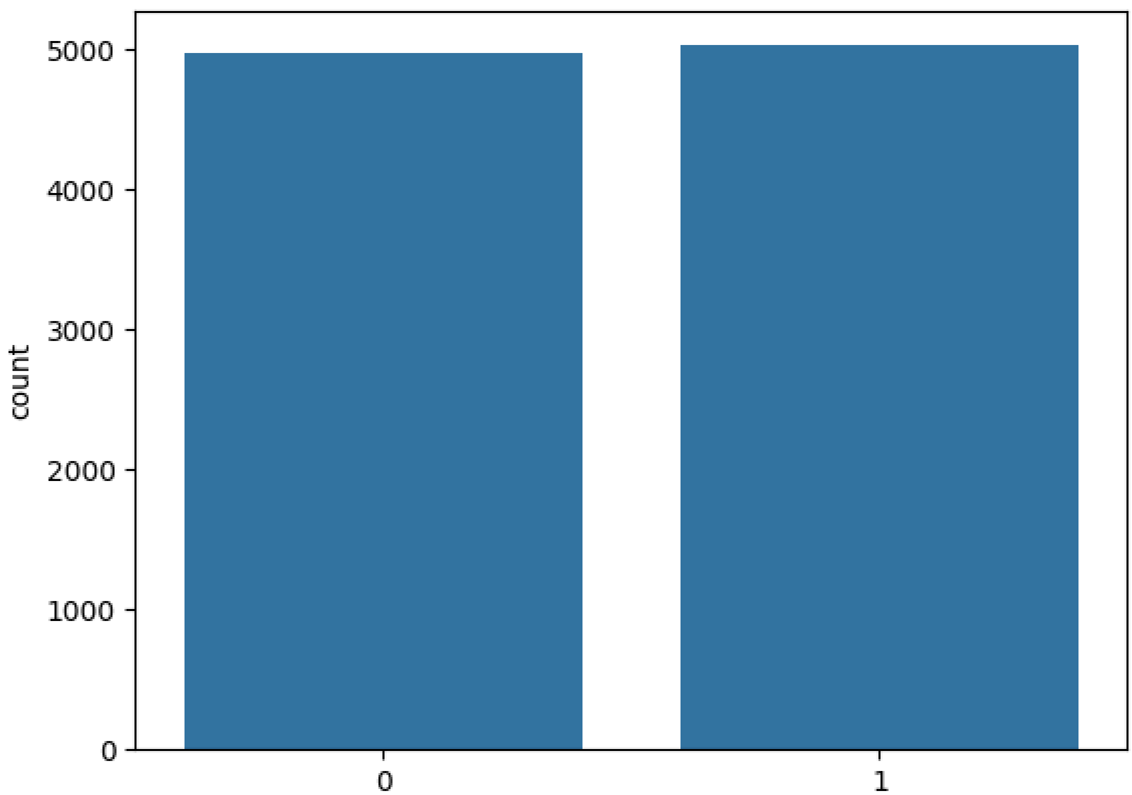
```
Blog data (external) loaded and preprocessed for contrastive learning.
Number of samples for contrastive learning: 611184
Number of labels for contrastive learning: 611184
```

In [20]:
```
# Test with subset of blog data (10K from 600k+)

texts_ctr_subset, _, labels_ctr_subset, _ = train_test_split(
    texts_ctr, labels_ctr, train_size=10000, stratify=labels_ctr, random_sta
)
# texts_ctr_subset, _, labels_ctr_subset, _ = train_test_split(
#     texts_ctr, labels_ctr, train_size=6000, stratify=labels_ctr, random_st
# )
print(f"Number of samples for contrastive learning subset: {len(texts_ctr_su
```

```
Number of samples for contrastive learning subset: 10000
```

In [21]:
```
# Check the distribution of labels in the subset
sns.countplot(x=labels_ctr_subset)
```

Out[21]: <Axes: ylabel='count'>



In [22]:
```
### PCA on external blog data
import joblib
import numpy as np
from sklearn.decomposition import PCA


# device = torch.device("mps" if torch.backends.mps.is_available() else "cpu
model = BertContrastiveModel().to(device)
model.eval()

dataset = SupervisedTextDataset(texts=texts_ctr_subset, labels=labels_ctr_su
```

```python
loader = DataLoader(
    dataset,
    batch_size=32,
    # batch_size=16,
    shuffle=False,
)

all_pooled = []
with torch.no_grad():
    for batch in loader:
        encoded, _ = batch
        pooled = model.encode(
            encoded["input_ids"].to(device),
            encoded["attention_mask"].to(device),
            encoded["token_type_ids"].to(device),
        )
        all_pooled.append(pooled.cpu().numpy())

all_pooled = np.vstack(all_pooled) # shape (N, 768)

# pca_full = PCA(n_components=768).fit(all_pooled)   # all_pooled: (N,768)
# cumvar = np.cumsum(pca_full.explained_variance_ratio_)
# # find smallest K where cumvar[K-1] >= desired_threshold
# desired = 0.95  # 95% variance
# K_95 = np.searchsorted(cumvar, desired) + 1
# print(f"Need {K_95} components to retain {desired*100:.0f}% of variance")

# Fit PCA
# pca = PCA(n_components=256)
pca = PCA(n_components=64)
pca.fit(all_pooled)
# Save PCA model
# joblib.dump(pca, "models/bert_pca_256.joblib")
joblib.dump(pca, "models/bert_pca_64.joblib")
print("PCA model saved.")
```

```
PCA model saved.
```

In [23]:

```python
# Create a custom dataset for contrastive learning on the training set
# This dataset will perform data augmentation on the input text samples
# (1 original + 1 augmented sample per text)


contrastive_dataset = SupervisedContrastiveTextDataset(
    texts_ctr_subset,
    labels_ctr_subset,
    tokenizer,
    max_length=128,
    augment=True,
)

contrastive_loader = DataLoader(contrastive_dataset, batch_size=16, shuffle=
# contrastive_loader = DataLoader(contrastive_dataset, batch_size=8, shuffle

# May change to a larger batch size to have more negative samples
# for contrastive learning
```

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

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

In [24]:
```
# 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 [25]:
```
##################################
# CONTRASTIVE PRE-TRAINING PHASE
##################################



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

# Run supervised contrastive pre-training
supervised_contrastive_pretrain(
    model,
    contrastive_loader,
    optimizer_ctr,
    device,
    # temperature=0.5,
    temperature=0.2,
    num_epochs=5,
    file_name="bert_supervised_contrastive_pretrained_final_pca.pth",
)

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

```
Supervised Contrastive Pre-training Epoch [1/5] Loss: 0.5511
Supervised Contrastive Pre-training Epoch [2/5] Loss: 0.4727
Supervised Contrastive Pre-training Epoch [3/5] Loss: 0.4484
Supervised Contrastive Pre-training Epoch [4/5] Loss: 0.4262
Supervised Contrastive Pre-training Epoch [5/5] Loss: 0.4084
Model saved at models/bert_supervised_contrastive_pretrained_final_pca.pth
Supervised Contrastive pre-training complete.
Supervised Contrastive pre-training complete. Model saved.
```

Supervised Fine-tuning

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

In [26]:
```
# Create custom datasets 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 remaining, 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]
)

batch_size = 8
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.

In [27]:
```
# Let computer cool down in 5 minutes with no activity
# print("Cooling down for 2 minutes...")
# time.sleep(120)
# print("Cool down complete. Resuming...")
```

In [28]:
```
# 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_supervised_contrastive_pretr
# pre_trained_path = os.path.join("models", "bert_supervised_contrastive_pre

# 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 supervised contrastive model weights.")
```

```
Loaded pre-trained supervised contrastive model weights.
```

In [29]:

```
##################################
# SUPERVISED FINE-TUNING PHASE
##################################


# Initialize the adam optimizer
optimizer_ft = optim.AdamW(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=10,
    patience=3,
    file_name="best_bert_supervised_final_pca.pth",
)

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

```
Epoch [1/10] - Train Loss: 0.6836, Val Loss: 0.6654, Val Acc: 0.5891
Best validation accuracy updated: 0.5891
Best supervised model updated and saved at models/best_bert_supervised_final
_pca.pth
Epoch [2/10] - Train Loss: 0.5957, Val Loss: 0.6648, Val Acc: 0.6221
Best validation accuracy updated: 0.6221
Best supervised model updated and saved at models/best_bert_supervised_final
_pca.pth
Epoch [3/10] - Train Loss: 0.4539, Val Loss: 0.6492, Val Acc: 0.6589
Best validation accuracy updated: 0.6589
Best supervised model updated and saved at models/best_bert_supervised_final
_pca.pth
Epoch [4/10] - Train Loss: 0.2358, Val Loss: 0.7766, Val Acc: 0.6764
Best validation accuracy updated: 0.6764
Best supervised model updated and saved at models/best_bert_supervised_final
_pca.pth
Epoch [5/10] - Train Loss: 0.0766, Val Loss: 1.0571, Val Acc: 0.6996
Best validation accuracy updated: 0.6996
Best supervised model updated and saved at models/best_bert_supervised_final
_pca.pth
Validation loss exceeds 1.0571053161524062. Early stopping triggered.
Supervised fine-tuning complete.
Best validation accuracy: 0.6996
Supervised fine-tuning complete. Model saved.
```

In [30]:

```
####################################
# 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 [31]:
```
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.

In [32]:
```
# Let computer cool down in 5 minutes with no activity
# print("Cooling down for 5 minutes...")
print("Cooling down for 1 minutes...")
# time.sleep(300)
time.sleep(60)
print("Cool down complete. Resuming...")
```

```
Cooling down for 1 minutes...
Cool down complete. Resuming...
```

Evaluation

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

In [33]:
```
# 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.")
```

In [34]:
```
# Load the supervised model weights
supervised_model_path = os.path.join("models", "best_bert_supervised_final_p
# 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))

# Load up the model (entire model, not just weights)
model = torch.load(supervised_model_path, weights_only=False)

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

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

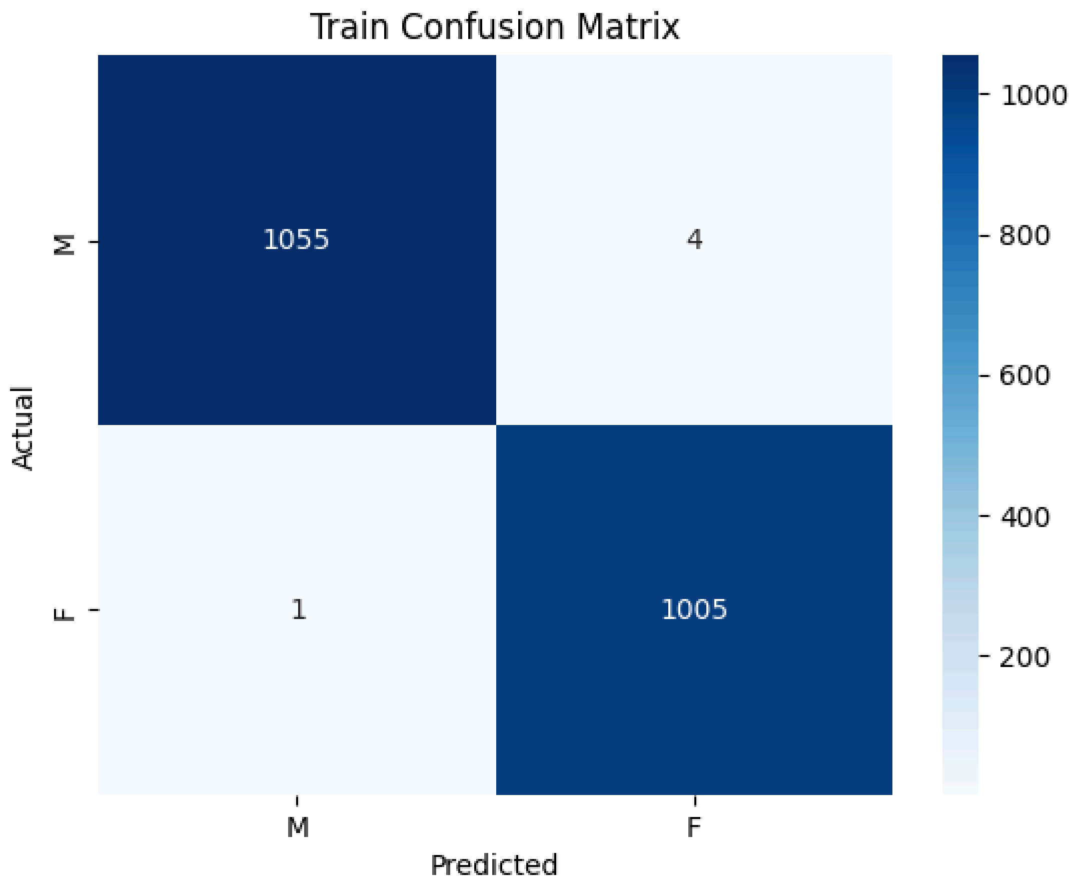
In [35]:
```
# current_state = model.state_dict()
# print("Current state of the model:")
# for key, value in current_state.items():
#     print(f"{key}: {value.size()}")
```

In [36]:
```
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 [37]:
```
########################################
# 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}")
```

```python
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",
    xticklabels=["M", "F"],
    yticklabels=["M", "F"],
)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Train Confusion Matrix")
plt.show()

print("=" * 30)
```

```
Evaluating on train set:
Loss: 0.0187
Accuracy: 0.9976
F1 Score: 0.9976
Classification Report:
              precision    recall  f1-score   support

           M       1.00      1.00      1.00      1059
           F       1.00      1.00      1.00      1006

    accuracy                           1.00      2065
   macro avg       1.00      1.00      1.00      2065
weighted avg       1.00      1.00      1.00      2065
```

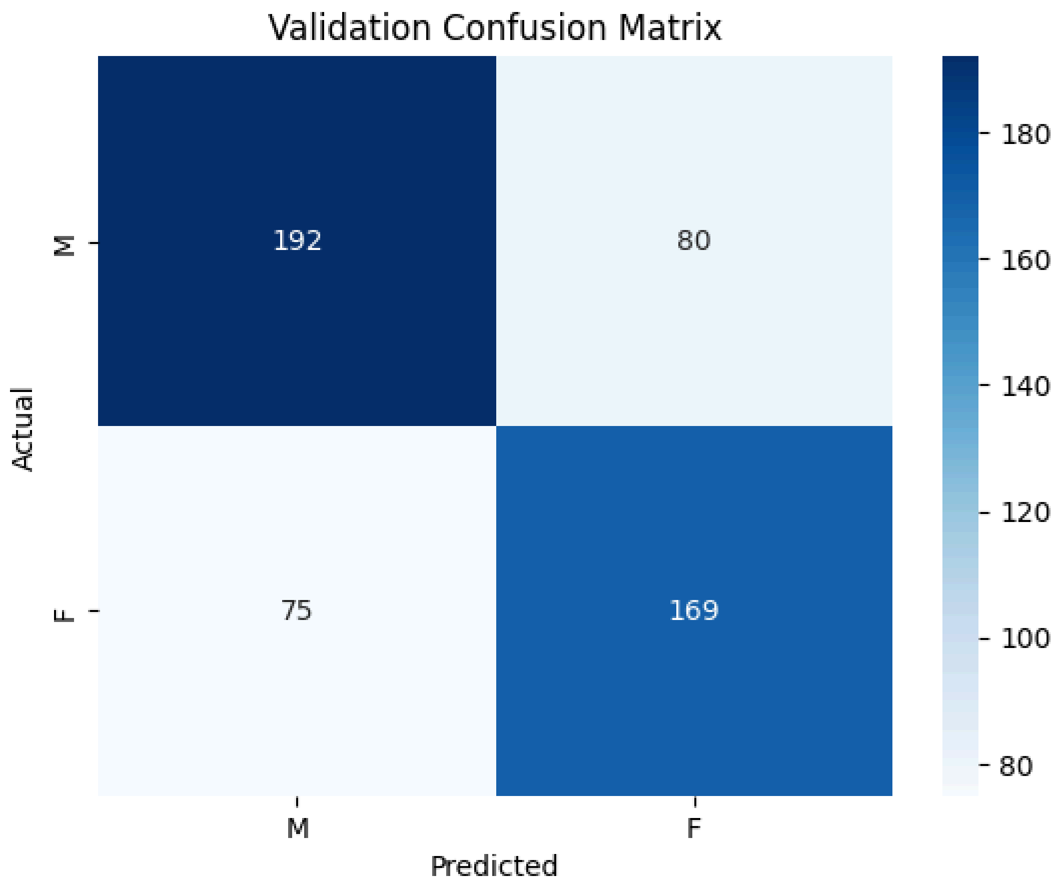


==============================

In [38]:

```
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",
    xticklabels=["M", "F"],
    yticklabels=["M", "F"],
)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Validation Confusion Matrix")
plt.show()
```

```
Evaluating on validation set:
Loss: 1.0571
Accuracy: 0.6996
F1 Score: 0.6997
Classification Report:
              precision    recall  f1-score   support

           M       0.72      0.71      0.71       272
           F       0.68      0.69      0.69       244

    accuracy                           0.70       516
   macro avg       0.70      0.70      0.70       516
weighted avg       0.70      0.70      0.70       516
```

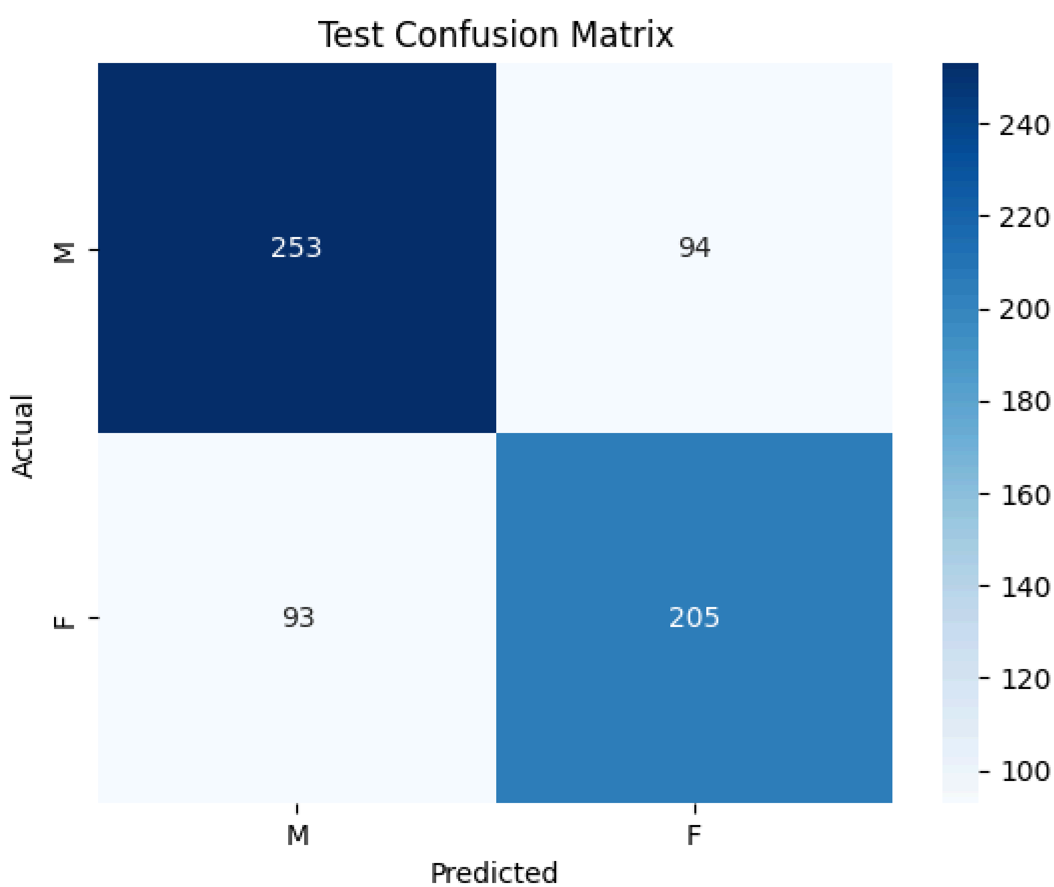


In [39]:

```
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",
    xticklabels=["M", "F"],
```

```
    yticklabels=["M", "F"],
)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Test Confusion Matrix")
plt.show()

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

```
Evaluating on test set:
Loss: 1.0499
Accuracy: 0.7101
F1 Score: 0.7101
Classification Report:
              precision    recall  f1-score   support

           M       0.73      0.73      0.73       347
           F       0.69      0.69      0.69       298

    accuracy                           0.71       645
   macro avg       0.71      0.71      0.71       645
weighted avg       0.71      0.71      0.71       645
```




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

In [40]:
```
# End the timer
end_time = time.time()
```

```
execution_time = end_time - start_time
execution_time_in_minutes = execution_time / 60
print(f"Pipeline total execution time: {execution_time_in_minutes:.2f} minut
# print(f"Pipeline total execution time: {execution_time:.2f} seconds")
print("All tasks completed successfully.")
```

```
Pipeline total execution time: 30.14 minutes
All tasks completed successfully.
```