Modul Praktikum Klasifikasi Teks

Part 1: Single-Label Classification & Part 2: Multi-Label Classification

Objective

This module consists of two parts:

1. **Single-Label Text Classification** using Naïve Bayes.
2. **Multi-Label Text Classification** using `scikit-multilearn`.

Each section will guide through data preprocessing, training, and evaluation.

Part 1: Single-Label Classification

1. Import Required Libraries

We will first import necessary libraries.

In [27]:
```
import pandas as pd
import numpy as np
import re
import string
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

2. Load Train, Validation, and Test Datasets

In [28]:
```
# Load datasets
train_data = pd.read_csv('./train_preprocess.csv')
val_data = pd.read_csv('./valid_preprocess.csv')
test_data = pd.read_csv('./test_preprocess.csv')

print('Train Data:', train_data.shape)
print('Validation Data:', val_data.shape)
print('Test Data:', test_data.shape)
```

```
Train Data: (810, 7)
Validation Data: (90, 7)
Test Data: (180, 7)
```

In [29]:
```
train_data.head()
```

Out[29]:

	sentence	fuel	machine	others	part	price	service
0	Saya memakai Honda Jazz GK5 tahun 2014 (perta...	neutral	neutral	positive	neutral	neutral	neutral
1	Avanza kenapa jadi boros bensin begini dah ah....	negative	neutral	neutral	neutral	neutral	neutral
2	saran ku dan pengalaman ku , mending beli mobi...	positive	positive	neutral	neutral	neutral	neutral
3	Dari segi harga juga pajero lebih mahal 30 jut...	neutral	neutral	neutral	neutral	positive	neutral
4	Kalo menurut gw enak pajero si	neutral	neutral	positive	neutral	neutral	neutral

3. Text Preprocessing

In [30]:
```
# Define text preprocessing function
def clean_text(text):
    text = text.lower()
    text = re.sub(r'\d+', '', text)
    text = text.translate(str.maketrans('', '', string.punctuation))
    text = text.strip()
    return text

# Apply preprocessing
train_data['clean_text'] = train_data['sentence'].apply(clean_text)
val_data['clean_text'] = val_data['sentence'].apply(clean_text)
test_data['clean_text'] = test_data['sentence'].apply(clean_text)
```

4. Feature Extraction & Training Single-Label Model

TFIDF with model : naive bayes, svm, KNN

In [31]:
```
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
```

```python
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score, KFold
import numpy as np
# TF-IDF Vectorizer
vectorizer = TfidfVectorizer()
X_train = vectorizer.fit_transform(train_data['clean_text'])
X_val = vectorizer.transform(val_data['clean_text'])
X_test = vectorizer.transform(test_data['clean_text'])

# Target labels
y_train = train_data['fuel']
y_val = val_data['fuel']
y_test = test_data['fuel']

param_grids = {
    'SVM': {
        'model': SVC(),
        'params': {
            'kernel': ['linear', 'rbf'],
            'C': [0.1, 1, 10]
        }
    },
    'KNN': {
        'model': KNeighborsClassifier(),
        'params': {
            'n_neighbors': [3, 5, 7],
            'weights': ['uniform', 'distance']
        }
    },
    'NB': {
        'model': MultinomialNB(),
        'params': {
            'alpha': [0.1, 0.5, 1.0]
        }
    }
}

kf = KFold(n_splits=5, shuffle=True, random_state=42)

best_models = {}
results = {}

for model_name, config in param_grids.items():
    print(f"Running GridSearchCV for {model_name}...")


    grid = GridSearchCV(config['model'], config['params'], cv=kf, scoring='accuracy')

    grid.fit(X_train, y_train)

    best_models[model_name] = grid.best_estimator_
    results[model_name] = grid.best_score_

    print(f"Best Params for {model_name}: {grid.best_params_}")
    print(f"Best Cross-Validation Accuracy: {grid.best_score_:.4f}\n")
```

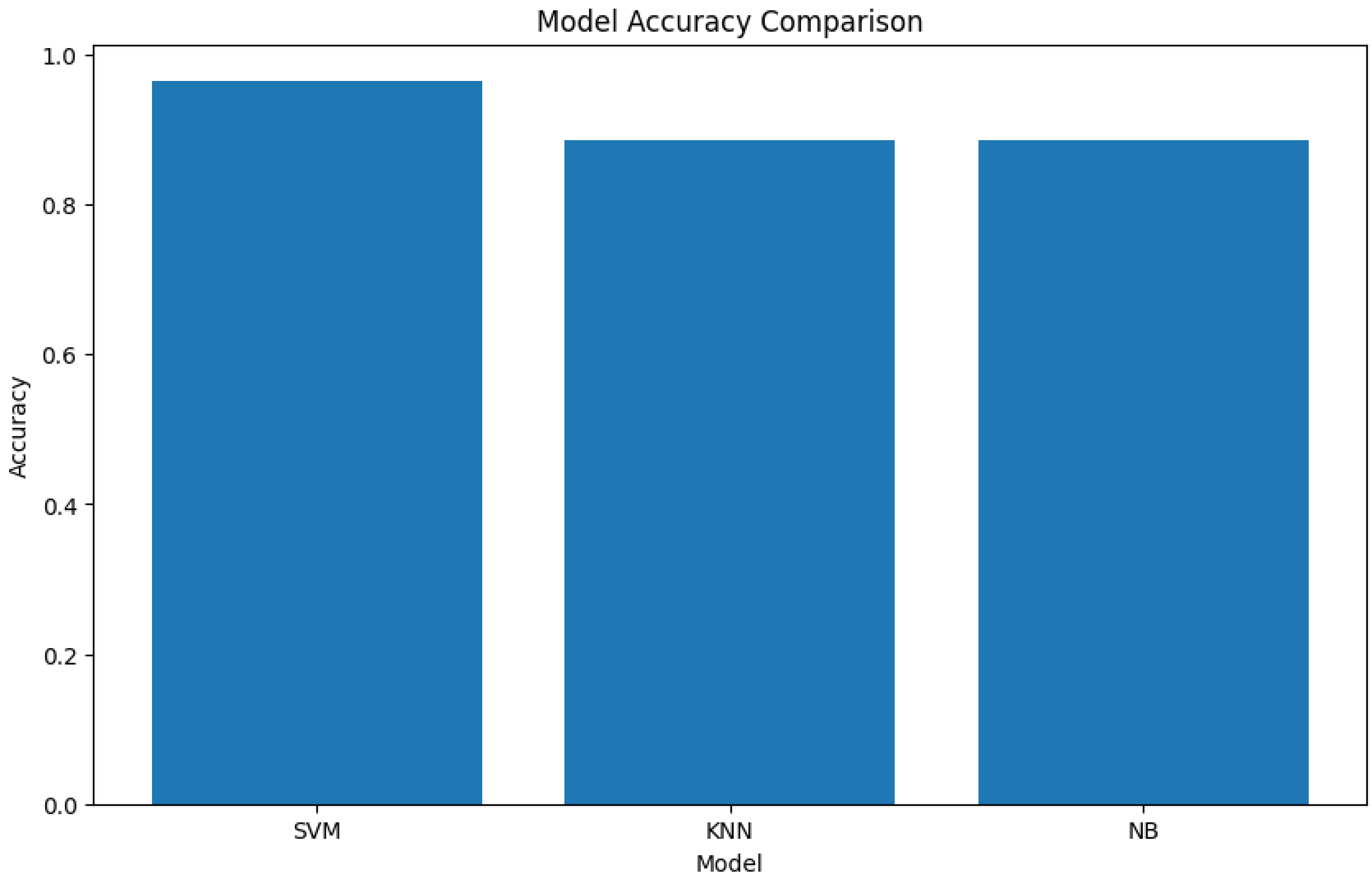
```
Running GridSearchCV for SVM...
Best Params for SVM: {'C': 10, 'kernel': 'linear'}
Best Cross-Validation Accuracy: 0.9654

Running GridSearchCV for KNN...
Best Params for KNN: {'n_neighbors': 7, 'weights': 'uniform'}
Best Cross-Validation Accuracy: 0.8852

Running GridSearchCV for NB...
Best Params for NB: {'alpha': 0.1}
Best Cross-Validation Accuracy: 0.8852
```

5. Evaluation of Single-Label Model

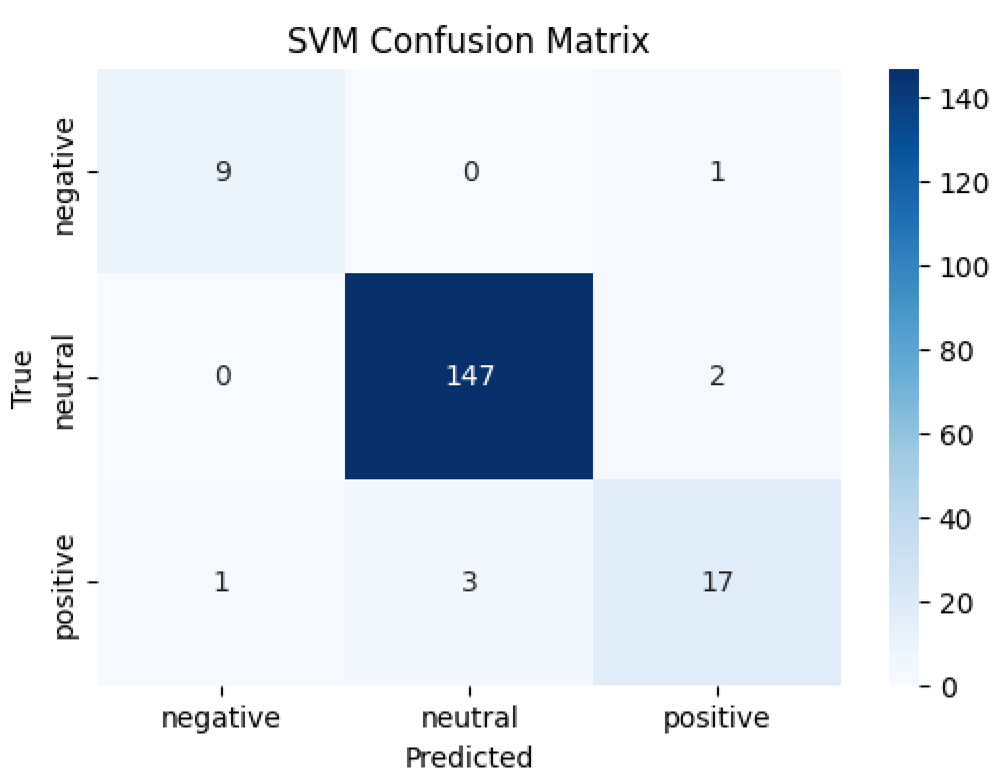
In [32]:

```python
# plot every model accuracy
label = ['negative', 'neutral', 'positive']
plt.figure(figsize=(10, 6))
plt.bar(results.keys(), results.values())
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.show()


for model_name, model in best_models.items():
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    print(f'{model_name} Accuracy on Test Set: {accuracy_score(y_test, y_pred):.4f}')
```

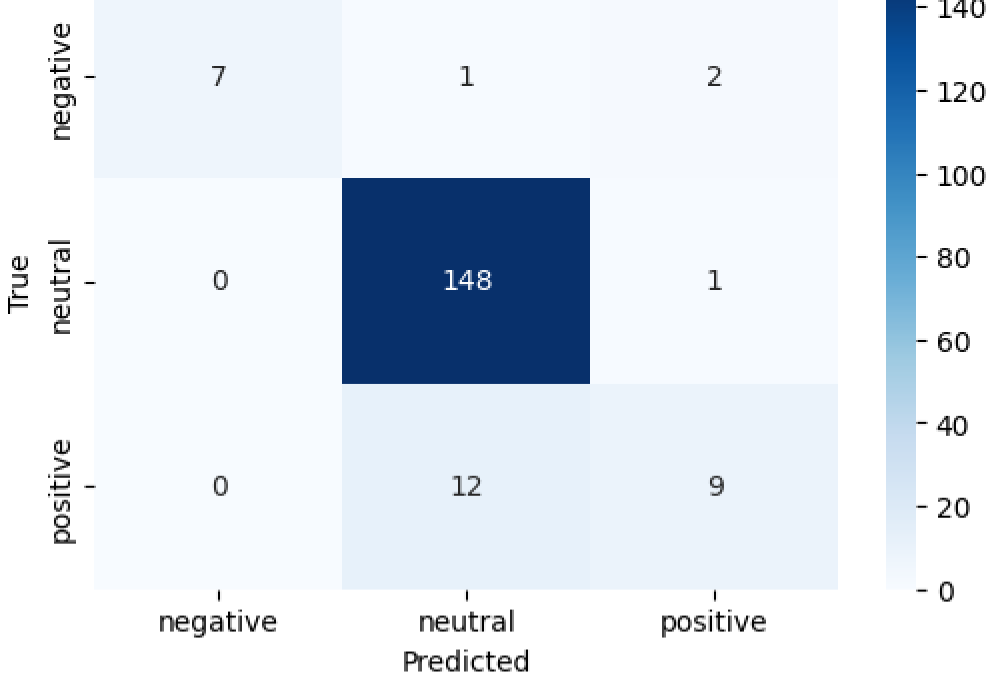
```python
    print(f'{model_name} Classification Report:')
    print(classification_report(y_test, y_pred))

    plt.figure(figsize=(6, 4))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True,
                fmt='d', cmap='Blues', xticklabels=label, yticklabels=label)
    plt.title(f'{model_name} Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()
```




```
SVM Accuracy on Test Set: 0.9611
SVM Classification Report:
              precision    recall  f1-score   support

    negative       0.90      0.90      0.90        10
     neutral       0.98      0.99      0.98       149
    positive       0.85      0.81      0.83        21

    accuracy                           0.96       180
   macro avg       0.91      0.90      0.90       180
weighted avg       0.96      0.96      0.96       180
```

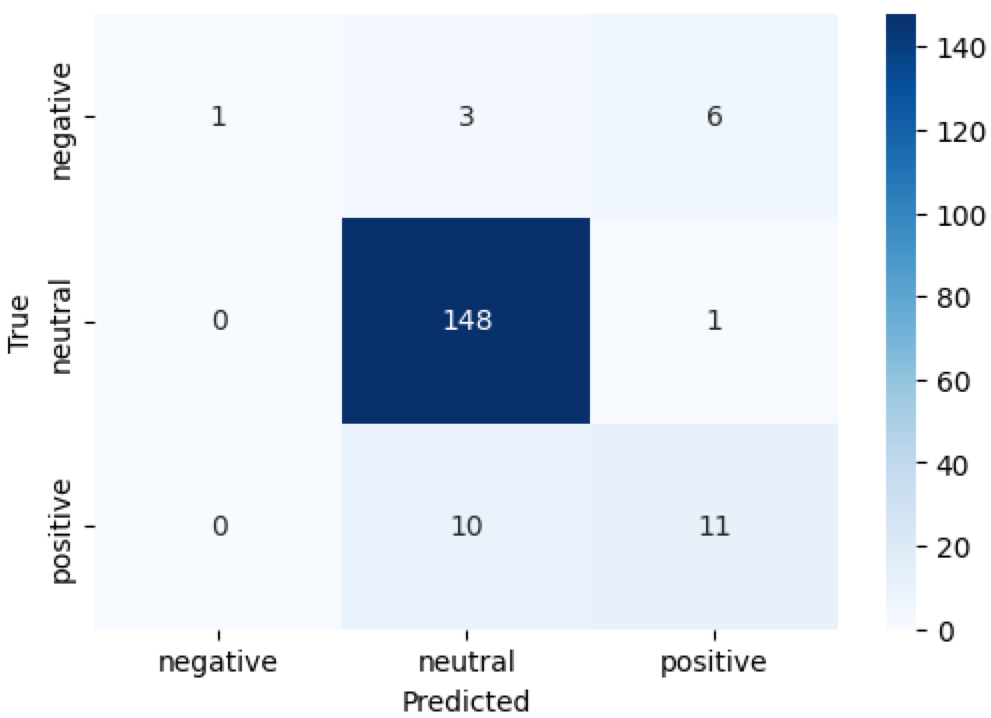



```
KNN Accuracy on Test Set: 0.9111
KNN Classification Report:
              precision    recall  f1-score   support

    negative       1.00      0.70      0.82        10
     neutral       0.92      0.99      0.95       149
    positive       0.75      0.43      0.55        21

    accuracy                           0.91       180
   macro avg       0.89      0.71      0.77       180
weighted avg       0.90      0.91      0.90       180
```




```
NB Accuracy on Test Set: 0.8889
NB Classification Report:
              precision    recall  f1-score   support

    negative       1.00      0.10      0.18        10
     neutral       0.92      0.99      0.95       149
    positive       0.61      0.52      0.56        21

    accuracy                           0.89       180
   macro avg       0.84      0.54      0.57       180
weighted avg       0.89      0.89      0.87       180
```

NB Confusion Matrix



In [33]:

```
# predict the test set
best_model = best_models['SVM']
best_model.fit(X_train, y_train)
y_pred = best_model.predict(X_test)
test_data['predicted'] = y_pred
test_data
```

Out[33]:

	sentence	fuel	machine	others	part	price	service	clean_text	predicted
0	Terios paling gagah . Apalagi warna merah meta...	neutral	neutral	positive	positive	neutral	neutral	terios paling gagah apalagi warna merah metalic	neutral
1	gue pakai mobilio . menurut gue , bener fun to...	neutral	neutral	positive	neutral	neutral	neutral	gue pakai mobilio menurut gue bener fun to d...	neutral
2	ya walaupun memiliki desain sporty kalau tingk...	neutral	neutral	negative	positive	neutral	neutral	ya walaupun memiliki desain sporty kalau tingk...	neutral
3	Xpander laku keras di pasar Indonesia .	neutral	neutral	positive	neutral	neutral	neutral	xpander laku keras di pasar indonesia	neutral
4	Kalau mau segala enak pakai Avanza saja , mas .	neutral	neutral	positive	neutral	neutral	neutral	kalau mau segala enak pakai avanza saja mas	neutral
...	...	...	...	...	...	...	...	...	...
175	kecewa sama bengkel suzuki bendan, garapan eng...	neutral	neutral	neutral	neutral	neutral	negative	kecewa sama bengkel suzuki bendan garapan engg...	neutral
176	Formo baris kedua, kursinya jelek banget.	neutral	neutral	neutral	negative	neutral	neutral	formo baris kedua kursinya jelek banget	neutral
177	Setahu saya Suzuki Splash tidak	neutral	neutral	neutral	negative	neutral	neutral	setahu saya suzuki splash tidak	neutral

177	dilengkapi den...	neutral	neutral	neutral	negative	neutral	neutral	dilengkapi den...	neutral
178	kalo dari eksterior nya saya lebih suka brio d...	neutral	neutral	neutral	negative	neutral	neutral	kalo dari eksterior nya saya lebih suka brio d...	neutral
179	Jazz irit bbm jadi irit kantong juga.	positive	neutral	neutral	neutral	neutral	neutral	jazz irit bbm jadi irit kantong juga	positive

180 rows × 9 columns

In [34]:
```
correct = test_data[test_data['fuel'] == test_data['predicted']]
incorrect = test_data[test_data['fuel'] != test_data['predicted']]
print(f"Correct Predictions: {len(correct)}")
print(f"Incorrect Predictions: {len(incorrect)}")
```

```
Correct Predictions: 173
Incorrect Predictions: 7
```

Part 2: Multi-Label Classification

6. Import Additional Libraries for Multi-Label Classification

In [35]:
```
#!pip install scikit-multilearn
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.metrics import multilabel_confusion_matrix
```

7. Preparing Multi-Label Data

In [36]:
```
# Define the labels for one-hot encoding
labels = ['fuel', 'machine', 'others', 'part', 'price', 'service']

# Apply one-hot encoding
train_encoded = pd.get_dummies(train_data, columns=labels, dtype=int)
val_encoded = pd.get_dummies(val_data, columns=labels, dtype=int)
test_encoded = pd.get_dummies(test_data, columns=labels, dtype=int)
```

In [37]:
```
train_encoded.head()
```

Out[37]:

	sentence	clean_text	fuel_negative	fuel_neutral	fuel_positive	machine_negative	machine_neutral	machine_positive	others_negativ
0	Saya memakai Honda Jazz GK5 tahun 2014 (perta...	saya memakai honda jazz gk tahun pertama mel...	0	1	0	0	1	0	
1	Avanza kenapa jadi boros bensin begini dah ah....	avanza kenapa jadi boros bensin begini dah ah ...	1	0	0	0	1	0	
2	saran ku dan pengalaman ku , mending beli mobi...	saran ku dan pengalaman ku mending beli mobil...	0	0	1	0	0	1	
3	Dari segi harga juga pajero lebih mahal 30 jut...	dari segi harga juga pajero lebih mahal jutaa...	0	1	0	0	1	0	
4	Kalo menurut gw enak pajero si	kalo menurut gw enak pajero si	0	1	0	0	1	0	

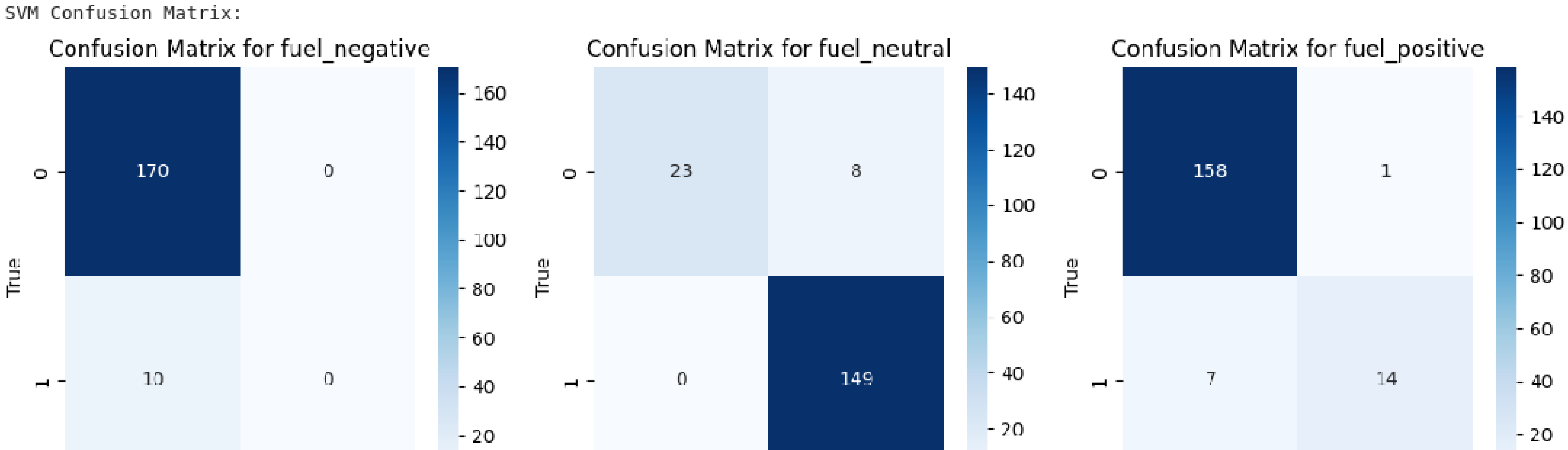
In [38]:
```
# Define label columns for multi-label classification
label_columns = ['fuel_negative', 'fuel_neutral', 'fuel_positive', 'machine_negative', 'machine_neutral','machine_positive']

y_train_multi = train_encoded[label_columns]
y_val_multi = val_encoded[label_columns]
y_test_multi = test_encoded[label_columns]
```

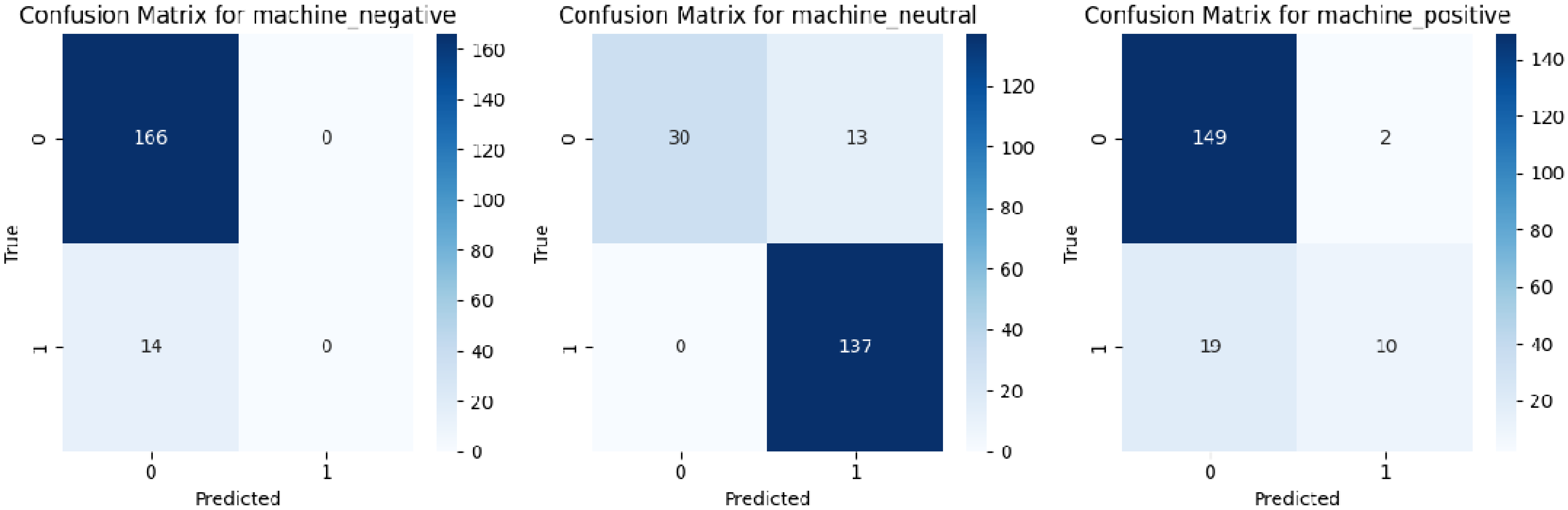
8. Training Multi-Label Classification Model

In [39]:
```
from sklearn.model_selection import KFold, cross_val_score
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.multiclass import OneVsRestClassifier
import numpy as np

multi_kf = KFold(n_splits=5, shuffle=True, random_state=42)
result = {}

models = {"SVM": SVC(), "KNN": KNeighborsClassifier(), "NB": MultinomialNB()}
```

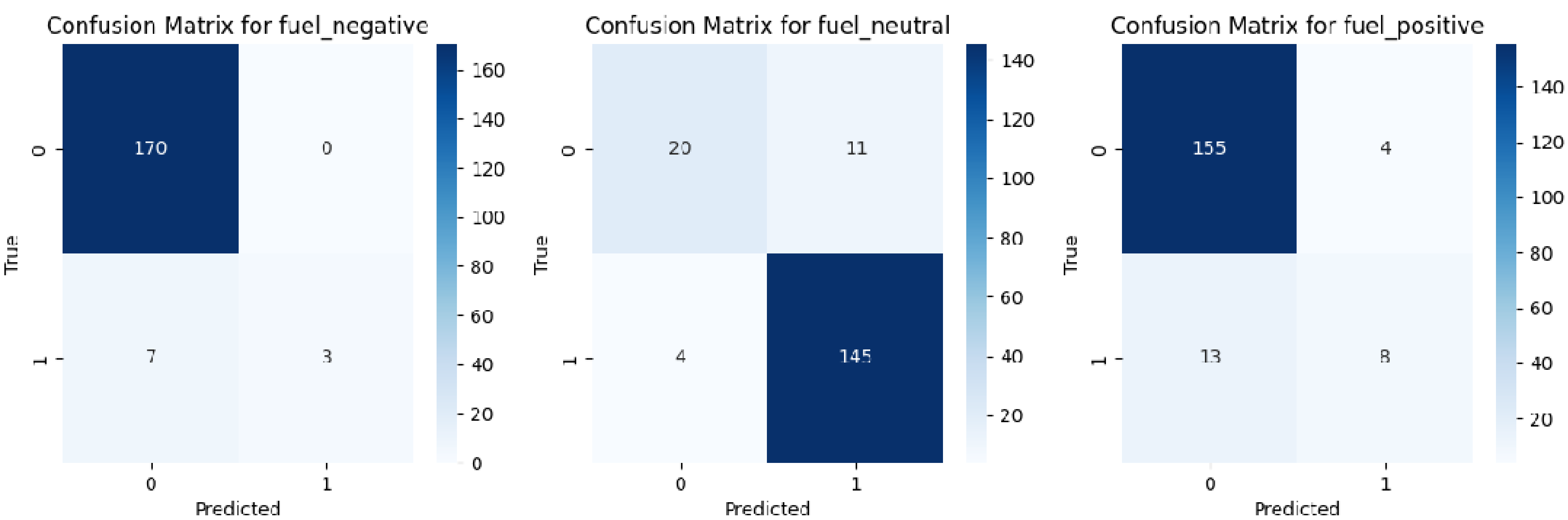
```python
for model_name, model in models.items():
    wrapped_model = BinaryRelevance(model)

    scores = cross_val_score(
        wrapped_model,
        X_train,
        y_train_multi,
        cv=multi_kf,
        scoring="accuracy",
        n_jobs=-1,
    )

    result[model_name] = scores
    print(
        f"{model_name} - Cross-Validation Accuracy: {np.mean(scores):.4f} ± {np.std(scores):.4f}"
    )

    wrapped_model.fit(X_train, y_train_multi)

    y_pred_multi = wrapped_model.predict(X_test)

    accuracy = accuracy_score(y_test_multi, y_pred_multi)
    print(f"{model_name} Final Accuracy:", accuracy)

    print(f"{model_name} Classification Report:")
    print(
        classification_report(
            y_test_multi, y_pred_multi, target_names=label_columns, zero_division=1
        )
    )

    print(f"{model_name} Confusion Matrix:")
    mcm = multilabel_confusion_matrix(y_test_multi, y_pred_multi)
    rows, cols = 2, 3  # 2 rows, 3 columns (adjustable if needed)
    fig, axes = plt.subplots(
        rows, cols, figsize=(cols * 4, rows * 4)
    )  # Adjust figure size
    # Flatten the axes array for easy iteration
    axes = axes.flatten()

    for i, (ax, label) in enumerate(zip(axes, label_columns)):
        # plt.figure(figsize=(5, 4))
        sns.heatmap(mcm[i], annot=True, fmt="d", cmap="Blues", ax=ax)
        # sns.heatmap(mcm[i], annot=True, fmt='d', cmap='Blues')
        ax.set_title(f"Confusion Matrix for {label}")
        ax.set_xlabel("Predicted")
        ax.set_ylabel("True")
        # plt.show()

    for j in range(len(label_columns), rows * cols):
        fig.delaxes(axes[j])
    plt.tight_layout()
    plt.show()


# test
```

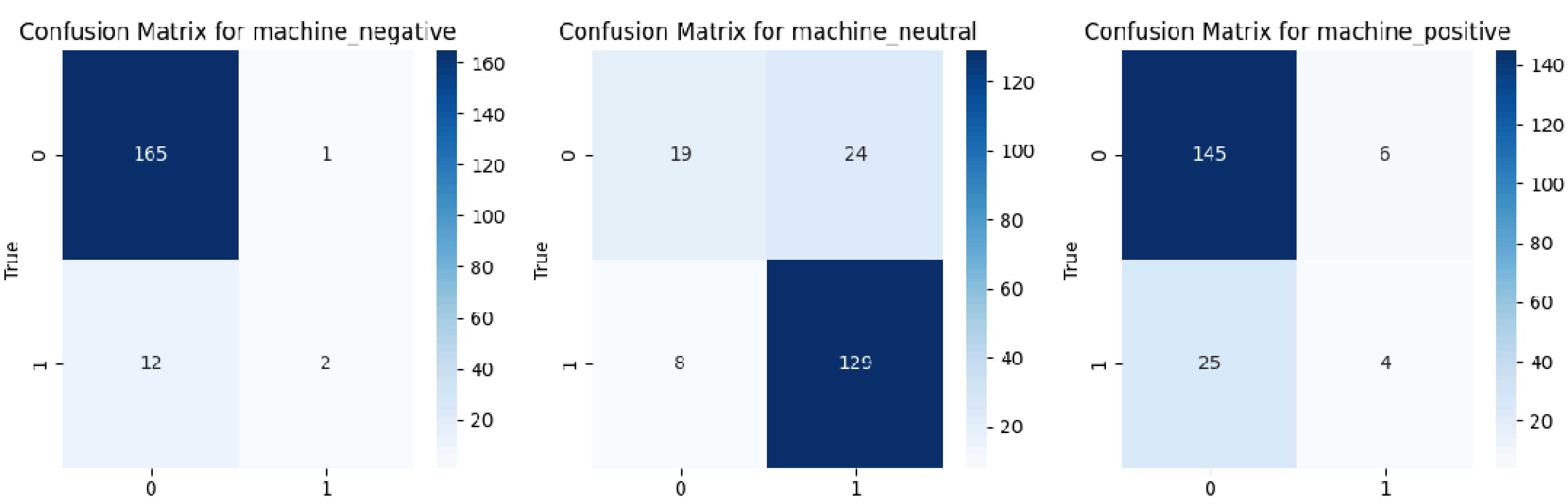
```
SVM - Cross-Validation Accuracy: 0.7247 ± 0.0252
SVM Final Accuracy: 0.75
SVM Classification Report:
                  precision    recall  f1-score   support

   fuel_negative       1.00      0.00      0.00        10
    fuel_neutral       0.95      1.00      0.97       149
   fuel_positive       0.93      0.67      0.78        21
machine_negative       1.00      0.00      0.00        14
 machine_neutral       0.91      1.00      0.95       137
machine_positive       0.83      0.34      0.49        29

       micro avg       0.93      0.86      0.89       360
       macro avg       0.94      0.50      0.53       360
    weighted avg       0.93      0.86      0.85       360
     samples avg       0.93      0.86      0.88       360

SVM Confusion Matrix:
```






```
KNN - Cross-Validation Accuracy: 0.7346 ± 0.0284
KNN Final Accuracy: 0.6555555555555556
KNN Classification Report:
                  precision    recall  f1-score   support

   fuel_negative       1.00      0.30      0.46        10
    fuel_neutral       0.93      0.97      0.95       149
   fuel_positive       0.67      0.38      0.48        21
machine_negative       0.67      0.14      0.24        14
 machine_neutral       0.84      0.94      0.89       137
machine_positive       0.40      0.14      0.21        29

       micro avg       0.86      0.81      0.84       360
       macro avg       0.75      0.48      0.54       360
    weighted avg       0.83      0.81      0.80       360
     samples avg       0.86      0.81      0.83       360

KNN Confusion Matrix:
```

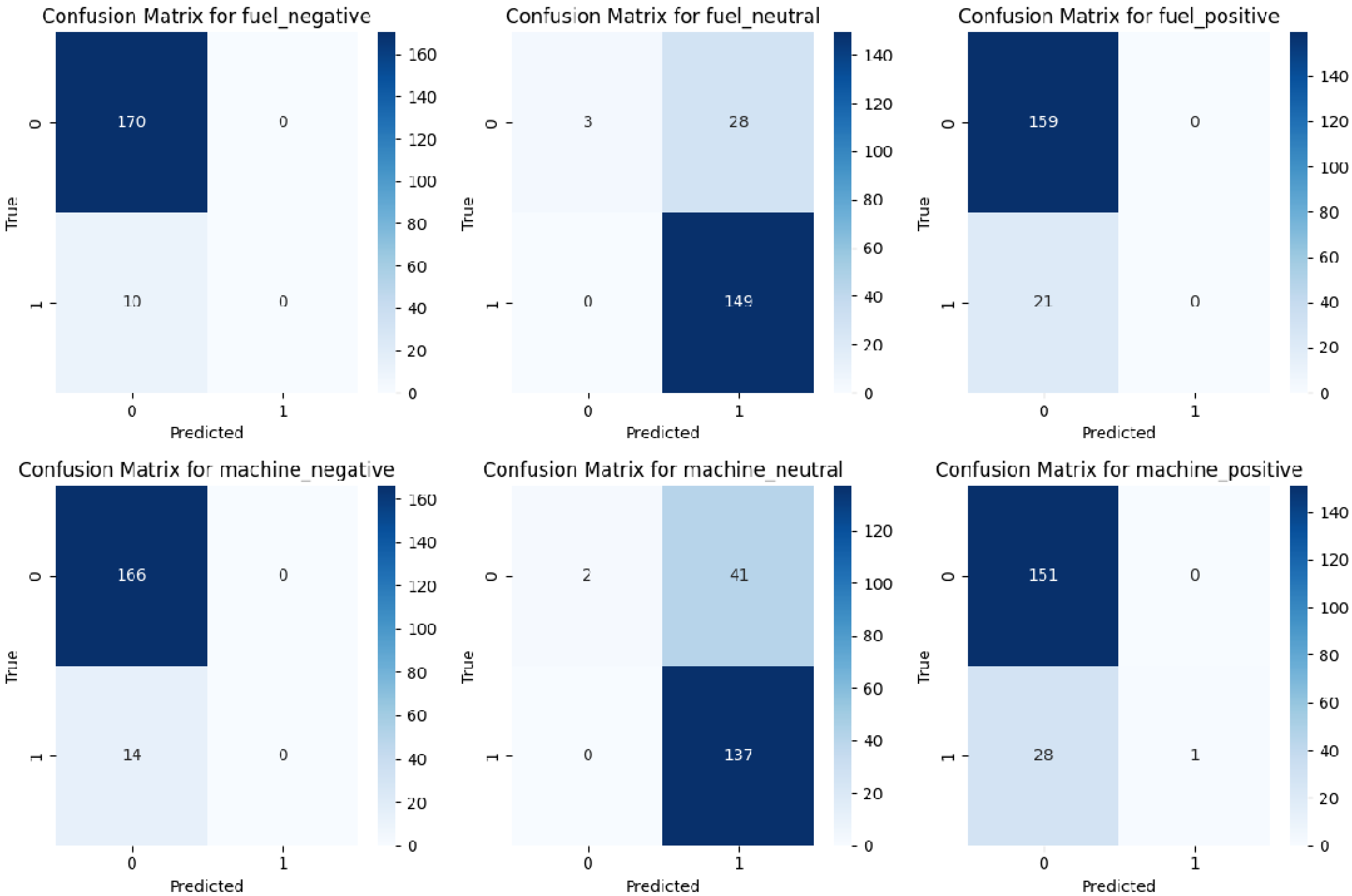





```
NB - Cross-Validation Accuracy: 0.6667 ± 0.0237
NB Final Accuracy: 0.6388888888888888
NB Classification Report:
                  precision    recall  f1-score   support

   fuel_negative       1.00      0.00      0.00        10
    fuel_neutral       0.84      1.00      0.91       149
```

```
   fuel_positive       1.00      0.00      0.00        21
machine_negative       1.00      0.00      0.00        14
 machine_neutral       0.77      1.00      0.87       137
machine_positive       1.00      0.03      0.07        29

       micro avg       0.81      0.80      0.80       360
       macro avg       0.94      0.34      0.31       360
    weighted avg       0.85      0.80      0.71       360
     samples avg       0.81      0.80      0.80       360
```

```
NB Confusion Matrix:
```



In [43]:

```python
from scipy.sparse import csr_matrix
y_pred_test = {}
for model_name, model in models.items():
    wrapped_model = BinaryRelevance(model)
    wrapped_model.fit(X_train, y_train_multi)
    y_pred_test[model_name] = wrapped_model.predict(X_test)



for model_name, y_pred in y_pred_test.items():
    print(f"\n{model_name} Predictions:\n")
    dense_array = y_pred.toarray()  # Convert sparse to dense
    print(dense_array)
```

```
SVM Predictions:

[[0 1 0 0 1 0]
 [0 1 0 0 1 0]
 [0 1 0 0 1 0]
 ...
 [0 1 0 0 1 0]
 [0 1 0 0 1 0]
 [0 0 1 0 1 0]]

KNN Predictions:

[[0 1 0 0 1 0]
 [0 1 0 0 1 0]
 [0 1 0 0 1 0]
 ...
 [0 1 0 0 1 0]
 [0 1 0 1 0 0]
 [0 0 1 0 1 0]]

NB Predictions:

[[0 1 0 0 1 0]
 [0 1 0 0 1 0]
 [0 1 0 0 1 0]
 ...
```

```
[0 1 0 0 1 0]
[0 1 0 0 1 0]
[0 0 0 0 1 0]]
```

Summary

This module demonstrated two parts:

1. **Single-label text classification** using Naïve Bayes.
2. **Multi-label text classification** using `scikit-multilearn` with Binary Relevance.

- Data was split into **train, validation, and test sets**.
- **Confusion matrices** were used for visualization.
- Further improvements could involve **deep learning approaches**.