Face Mask Project Documentation

Face Mask Detection Data set

In recent trend in worldwide Lockdowns due to COVID19 outbreak, as Face Mask has became mandatory for everyone while roaming outside, approach of Deep Learning for Detecting Faces With and Without mask were a good trendy practice. Here I have created a model that detects face mask trained on 7553 images with 3 color channels (RGB).
On Custom CNN architecture Model training accuracy reached 94% and Validation accuracy 96%.

Content:

The dataset consists of 7553 RGB images in 2 folders as with_mask and without_mask. Images are named as label with_mask and without_mask. Images of faces with mask are 3725 and images of faces without mask are 3828.

- 3760 Images of Face with Mask
- 3828 Images of Face without Mask.

Overview:

In this project we used python language to implement 'Face Mask Detection' and we loaded the dataset on drive and used cloud compiler colab, We Created class called FaceMaskClassifier that contain methods like:

1- Load_data(self)
Which loads data from the drive and makes labels for data and sum preprocessing like resizing ,converting colors , normalization and reshaping.
2- visualize_results(self)
which visualize samples with labeled data and *# If Convolutional neural network history is provided, plot learning curves*
3- plot_confusion_matrix(self, y_true, y_pred, title)
which visualize the confusion matrix for each model in the project
4- run_complete_analysis(self)
In this method we call all methods to make a visualization and training the models.
5- train_knn(self, n_neighbors=5)
which take the n_neighbors for the model and training the create k-nearest neighbors for the model
6- train_logistic_regression(self)
Which make model for logistic regression
7- train_SVM(self)
which train support vector machine model on our data

8- build_cnn(self)
   Which building and training Convolutional Neural Network
9- main()
   main function to make an instance from the class and call a run_complete_analysis

project implementation:

Step1: importing the libraries which we used in the program:

```python
# Import required libraries
import os
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.image as mpimg
import cv2
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
from PIL import Image
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
from sklearn.metrics import confusion_matrix
from tensorflow.keras.utils import to_categorical
```

Step2:we will implement the class with initialization methods which call load_data and make labels for classes :

```python
class FaceMaskClassifier :

    def __init__(self):
        # Load and prepare data
        self.load_data()
        self.class_names = ['without_mask','with_mask']
```

Step3: we will start with load_data() Which loads data from the drive and make labels for data and sum preprocessing like resizing ,converting colors , normalization and reshaping used in this method we used some functions like os.listdir() which lists the names of the images in the folder we have , imread() which read the image from the path we have , resize () which resize the images cv2.cvtColor() to convert images from BGR to RGB and make normalization and reshape as we used in the image.

```
def load_data(self):

  path1 = r'/content/drive/MyDrive/data/with_mask'
  path2 = r'/content/drive/MyDrive/data/without_mask'
  self.with_mask_files = os.listdir(path1)
  self.without_mask_files = os.listdir(path2)

  self.with_mask_labels = [1] * len(self.with_mask_files)
  self.without_mask_labels = [0] * len(self.without_mask_files)
  self.all_labels = self.with_mask_labels + self.without_mask_labels



  self.data = []
  self.with_mask_path = r'/content/drive/MyDrive/data/with_mask/'
  for img_file in self.with_mask_files:
    image = cv2.imread(self.with_mask_path + img_file)
    image = cv2.resize(image,(128,128))
    image = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
    image = np.array(image)
    self.data.append(image)


  self.without_mask_path = r'/content/drive/MyDrive/data/without_mask/'


  for img_file in self.without_mask_files:
    image = cv2.imread(self.without_mask_path + img_file)
    image = cv2.resize(image,(128,128))
    image = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
    image = np.array(image)
    self.data.append(image)


  self.X = np.array(self.data)
  self.Y = np.array(self.all_labels)

  self.x_train, self.x_test, self.y_train, self.y_test = train_test_split(self.X, self.Y, test_size=0.2,stratify = self.Y, random_state=42)
```

```
# Normalize pixel values
self.x_train = self.x_train.astype('float32') / 255.0
self.x_test = self.x_test.astype('float32') / 255.0


# Reshape for traditional classifiers
self.x_train_flat = self.x_train.reshape(self.x_train.shape[0], -1)
self.x_test_flat = self.x_test.reshape(self.x_test.shape[0], -1)
```

Step4: we created the method “visualize_results” which is used to visualize our outputs like:

Samples of our labeled dataset and CNN history(val_acc,acc,loss)

```
def visualize_results(self, history=None):
    """Visualize training results and examples"""
    # Set up the figure
    plt.figure(figsize=(15, 10))

    # Plot sample images
    for i in range(10):
        plt.subplot(2, 5, i + 1)
        plt.imshow(self.x_train[i], cmap='gray')
        plt.title(self.class_names[self.y_train[i]])
        plt.axis('off')

    plt.tight_layout()
    plt.show()

    # If neural network history is provided, plot learning curves
    if history is not None:
        plt.figure(figsize=(12, 4))

        plt.subplot(1, 2, 1)
        plt.plot(history.history['accuracy'], label='Training')
        plt.plot(history.history['val_accuracy'], label='Validation')
        plt.title('Model Accuracy')
        plt.xlabel('Epoch')
        plt.ylabel('Accuracy')
        plt.legend()

        plt.subplot(1, 2, 2)
        plt.plot(history.history['loss'], label='Training')
        plt.plot(history.history['val_loss'], label='Validation')
        plt.title('Model Loss')
        plt.xlabel('Epoch')
        plt.ylabel('Loss')
        plt.legend()

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

Step5: plot_confusion_matrix () → We used this method to plot the confusion matrix of each model which displays the accuracy of the model through showing the true positive, false positive, true negative and false negative predictions .

```
def plot_confusion_matrix(self, y_true, y_pred, title):
    """Plot confusion matrix"""
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=self.class_names,
                yticklabels=self.class_names)
    plt.title(title)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

Step6: train_knn() → In this method we used the KNeighborsClassifier from sklearn.neighbors

Which enables us to train the KNN algorithm on our data

```
def train_knn(self, n_neighbors=5):
    """Train K-Nearest Neighbors classifier"""
    print("Training KNN classifier...")
    self.knn = KNeighborsClassifier(n_neighbors=n_neighbors)
    self.knn.fit(self.x_train_flat, self.y_train)

    # Make predictions
    y_pred = self.knn.predict(self.x_test_flat)

    # Calculate metrics
    accuracy = accuracy_score(self.y_test, y_pred)
    precision, recall, f1, _ = precision_recall_fscore_support(self.y_test, y_pred, average='weighted')

    print(f"KNN Metrics:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-score: {f1:.4f}")

    return accuracy, precision, recall, f1
```

Step7: train_logistic_regression() → In this method we used the LogisticRegression

from sklearn.linear_model ,Which enables us to train the logistic regression algorithm on our data.

```
def train_logistic_regression(self):
    """Train Logistic Regression classifier"""
    print("Training Logistic Regression classifier...")
    self.lr = LogisticRegression(multi_class='multinomial', max_iter=1000)
    self.lr.fit(self.x_train_flat, self.y_train)

    # Make predictions
    y_pred = self.lr.predict(self.x_test_flat)

    # Calculate metrics
    accuracy = accuracy_score(self.y_test, y_pred)
    precision, recall, f1, _ = precision_recall_fscore_support(self.y_test, y_pred, average='weighted')

    print(f"Logistic Regression Metrics:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-score: {f1:.4f}")
```

Step8: train_SVM()→ In this method we used the SVC

from sklearn.svm, Which enables us to train the support vector machine algorithm on our data.

```python
def train_SVM (self):
    print ("Training SVM classifier...")
    self.svm = SVC(kernel='rbf', C=1.0, gamma='scale')
    self.svm.fit(self.x_train_flat, self.y_train)

    # Make predictions
    y_pred = self.svm.predict(self.x_test_flat)

    # Calculate metrics
    accuracy = accuracy_score(self.y_test, y_pred)
    precision, recall, f1, _ = precision_recall_fscore_support(self.y_test, y_pred, average='weighted')

    print(f"SVM Metrics:")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-score: {f1:.4f}")
    return accuracy, precision, recall, f1
```

Step9: build_cnn() → This method constructs and trains a Convolutional Neural Network (CNN) for image classification tasks. It is designed to process input images of shape (128, 128, 3) and classify them into two categories. The method employs Keras' Sequential API to build the CNN architecture and includes training, evaluation, and metric calculation.

```python
def build_cnn(self):
    """Build and train Convolutional Neural Network"""
    print("Building and training Convolutional Neural Network...")
    self.cnn = Sequential()
    self.cnn.add(Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(128,128,3)))
    self.cnn.add(MaxPooling2D(pool_size=(2,2)))

    self.cnn.add(Conv2D(64, kernel_size=(3,3), activation='relu'))
    self.cnn.add(MaxPooling2D(pool_size=(2,2)))

    self.cnn.add(Flatten())

    self.cnn.add(Dense(128, activation='relu'))
    self.cnn.add(Dropout(0.5))

    self.cnn.add(Dense(64, activation='relu'))
    self.cnn.add(Dropout(0.5))
    ##        number_of_calsses,(sigmoid or softmax)---> sigmoid: works with low number of classes , softmax: works better with multi-class data
    self.cnn.add(Dense(2, activation='sigmoid'))

    self.cnn.compile(optimizer='adam',
                          loss='sparse_categorical_crossentropy',
                          metrics=['accuracy'])
    # Train the model
    history = self.cnn.fit(self.x_train, self.y_train,
                    epochs=6,    #if we increase it the val_acc and the acc should increase
                    validation_split=0.1)
    # Evaluate the model
    test_loss, test_accuracy = self.cnn.evaluate(self.x_test, self.y_test)
    y_pred = np.argmax(self.cnn.predict(self.x_test), axis=1)
    precision, recall, f1, _ = precision_recall_fscore_support(self.y_test, y_pred, average='weighted')

    print(f"\nConvolutinoal Neural Network Metrics:")
    print(f"Test accuracy: {test_accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-score: {f1:.4f}")

    return history, test_accuracy, precision, recall, f1
```

Step10: run_complete_analysis() → This is the main method in our class which we used to perform all the pervious methods in addition to compare between all those algorithms

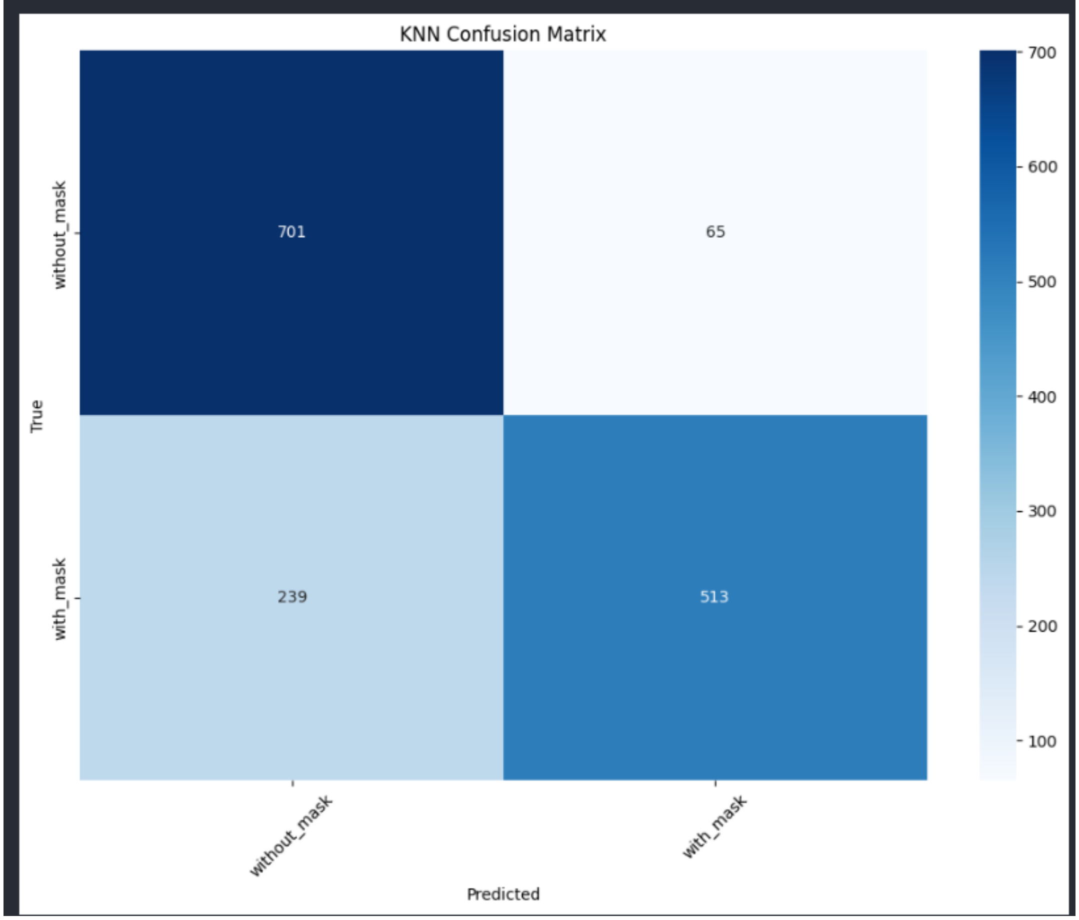
```
def run_complete_analysis(self):
    """Run complete analysis with all methods"""
    # 1. Visualize sample images
    print("Visualizing sample images...")
    self.visualize_results()

    # 2. Train and evaluate KNN
    knn_metrics = self.train_knn()
    y_pred_knn = self.knn.predict(self.x_test_flat)
    self.plot_confusion_matrix(self.y_test, y_pred_knn, 'KNN Confusion Matrix')

    # 3. Train and evaluate Logistic Regression
    lr_metrics = self.train_logistic_regression()
    y_pred_lr = self.lr.predict(self.x_test_flat)
    self.plot_confusion_matrix(self.y_test, y_pred_lr, 'Logistic Regression Confusion Matrix')

    # 4. Train and evaluate SVM
    svm_metrices = self.train_SVM()
    y_pred_lr = self.svm.predict(self.x_test_flat)
    self.plot_confusion_matrix(self.y_test, y_pred_lr, 'SVM Confusion Matrix')

    # 5.Train and evaluate Convolutional Neural Networks
    cnn_history, *cnn_metrics = self.build_cnn()
    y_pred_cnn = np.argmax(self.cnn.predict(self.x_test), axis=1)
    self.plot_confusion_matrix(self.y_test, y_pred_cnn, 'CNN Confusion Matrix')


    # 6. Visualize neural network training history
    self.visualize_results(cnn_history)

    # 8. Compare all methods
    methods = ['KNN', 'Logistic Regression','SVM','CNN']
    metrics = [knn_metrics, lr_metrics,svm_metrices ,cnn_metrics]

    print("\nComparison of All Methods:")
    print("Method       Accuracy  Precision  Recall    F1-Score")
    print("-" * 50)
    for method, metric in zip(methods, metrics):
        print(f"{method:<12} {metric[0]:.4f}   {metric[1]:.4f}    {metric[2]:.4f}   {metric[3]:.4f}")
```

Step11: main fun() → Last but not least the main function where we can create an instance from our class and call the run_complete_analysis() method

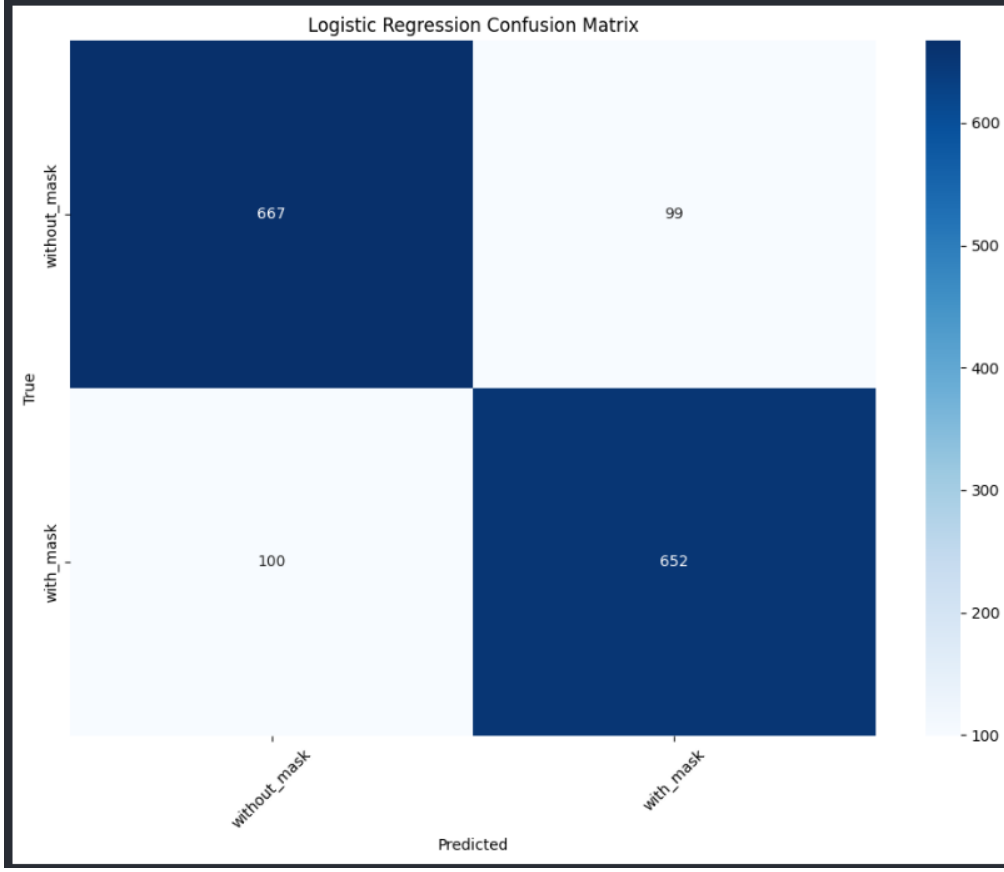
```
# Run the complete analysis
if __name__ == "__main__":

    classifier = FaceMaskClassifier()
    classifier.run_complete_analysis()
```

Output:

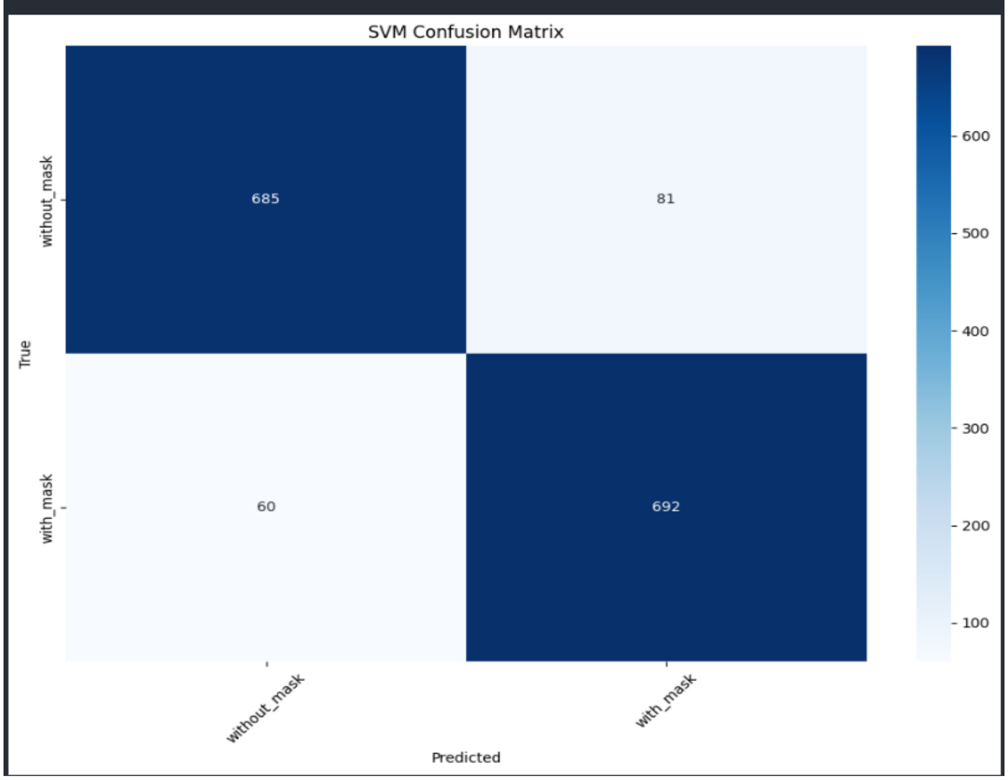

```
Training KNN classifier...
KNN Metrics:
Accuracy: 0.7997
Precision: 0.8160
Recall: 0.7997
F1-score: 0.7968
```



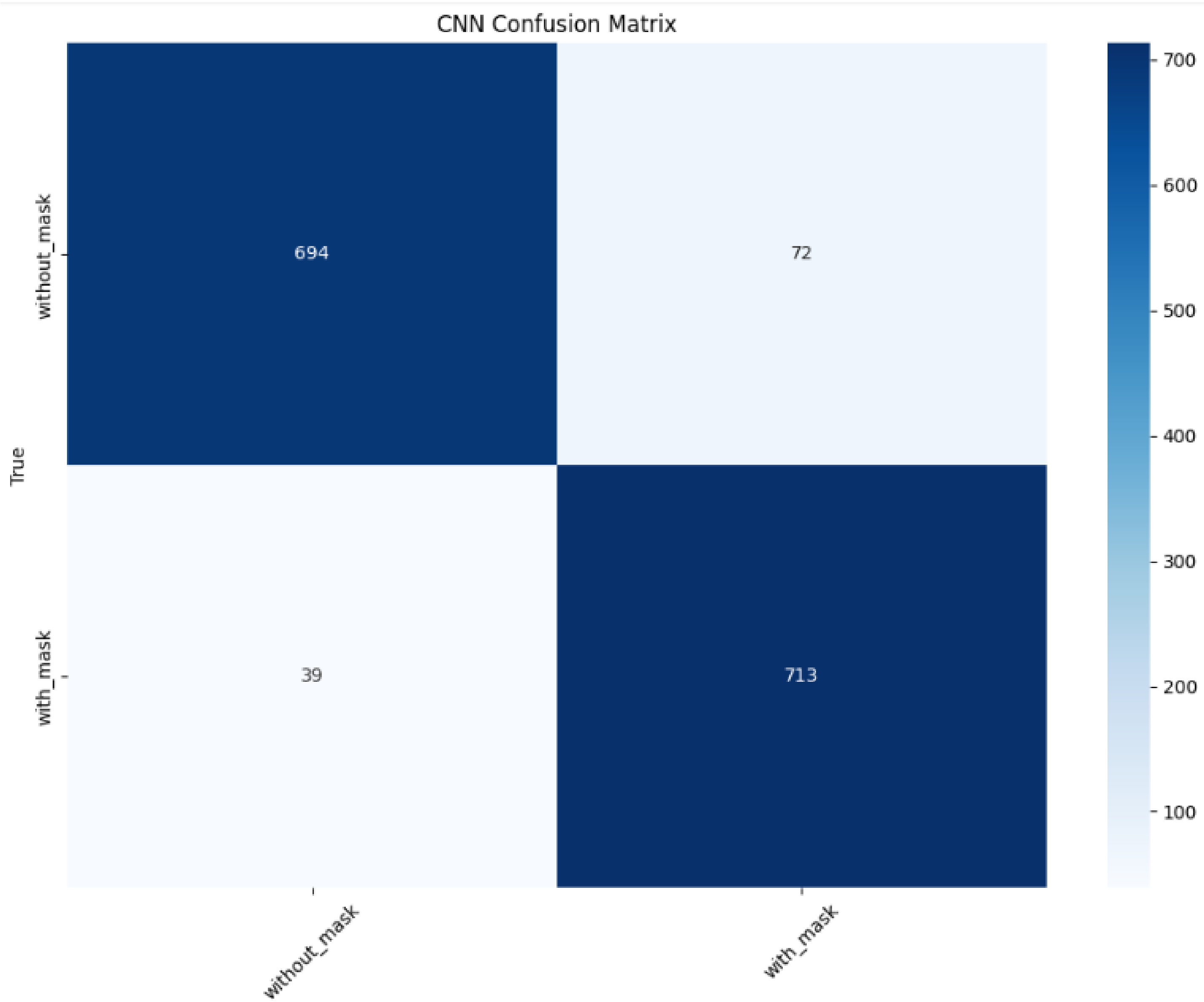
```
Training Logistic Regression classifier...
Logistic Regression Metrics:
Accuracy: 0.8689
Precision: 0.8689
Recall: 0.8689
F1-score: 0.8689
```

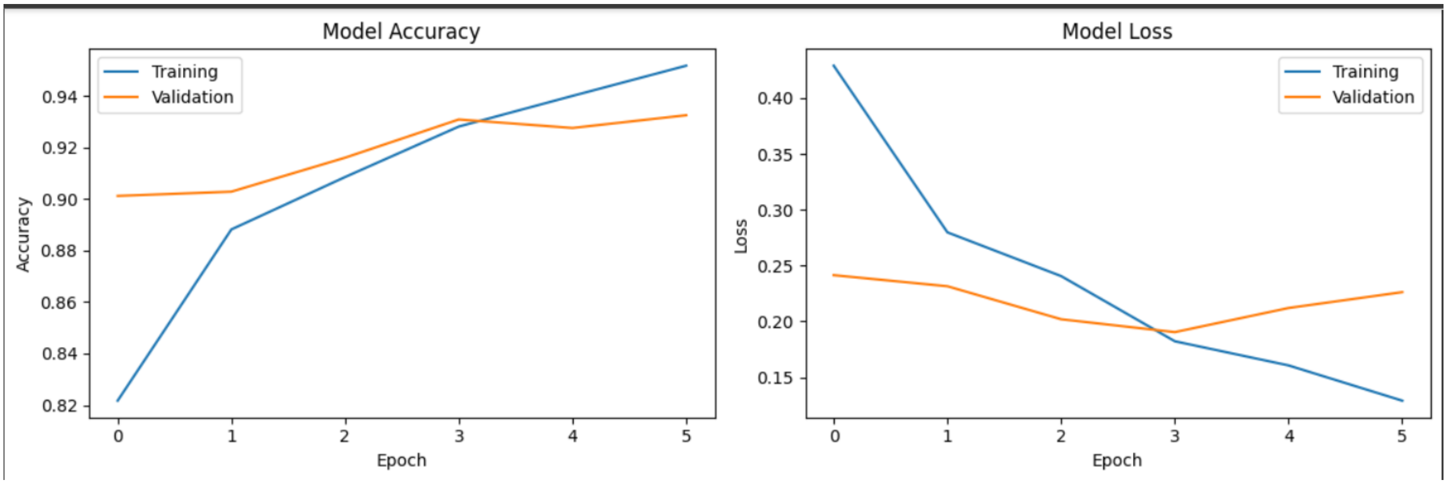



```
Training SVM classifier...
SVM Metrics:
Accuracy: 0.9071
Precision: 0.9075
Recall: 0.9071
F1-score: 0.9071
```



```
Building and training Convolutional Neural Network...
Epoch 1/6
171/171 ━━━━━━━━━━━━━━━━━━━━ 145s 838ms/step - accuracy: 0.7463 - loss: 0.5847 - val_accuracy: 0.9012 - val_loss: 0.2414
Epoch 2/6
171/171 ━━━━━━━━━━━━━━━━━━━━ 199s 820ms/step - accuracy: 0.8817 - loss: 0.2895 - val_accuracy: 0.9028 - val_loss: 0.2315
Epoch 3/6
171/171 ━━━━━━━━━━━━━━━━━━━━ 137s 792ms/step - accuracy: 0.9032 - loss: 0.2424 - val_accuracy: 0.9160 - val_loss: 0.2020
Epoch 4/6
171/171 ━━━━━━━━━━━━━━━━━━━━ 138s 809ms/step - accuracy: 0.9294 - loss: 0.1804 - val_accuracy: 0.9308 - val_loss: 0.1904
Epoch 5/6
171/171 ━━━━━━━━━━━━━━━━━━━━ 145s 825ms/step - accuracy: 0.9392 - loss: 0.1642 - val_accuracy: 0.9275 - val_loss: 0.2121
Epoch 6/6
171/171 ━━━━━━━━━━━━━━━━━━━━ 141s 824ms/step - accuracy: 0.9478 - loss: 0.1353 - val_accuracy: 0.9325 - val_loss: 0.2263
48/48 ━━━━━━━━━━━━━━━━━━━━ 11s 237ms/step - accuracy: 0.9301 - loss: 0.2266
48/48 ━━━━━━━━━━━━━━━━━━━━ 10s 204ms/step

Convolutinoal Neural Network Metrics:
Test accuracy: 0.9269
Precision: 0.9277
Recall: 0.9269
F1-score: 0.9269
48/48 ━━━━━━━━━━━━━━━━━━━━ 11s 228ms/step
```





Comparison of All Methods:

Method	Accuracy	Precision	Recall	F1-Score
KNN	0.7997	0.8160	0.7997	0.7968
Logistic Regression	0.8689	0.8689	0.8689	0.8689
SVM	0.9071	0.9075	0.9071	0.9071
CNN	0.9269	0.9277	0.9269	0.9269

Conclusion

The Face Mask Detection Project serves as a vital step in addressing public health concerns during the pandemic. By leveraging advanced machine learning and deep learning models, this project offers an effective solution for real-time mask compliance detection. The system's high accuracy and flexibility make it suitable for deployment in various domains, including surveillance, healthcare, and public transportation. With comprehensive documentation and code, this project can be easily extended and adapted for future needs.

- **Dataset link**: Face Mask Dataset

- **Git-Hub repo link**: Face Mask Detection Project

Team Members

- **Eslam Saad Gomaa**
- **Youssef Ahmed Khalil**