PRML MINOR PROJECT REPORT MASK NO-MASK

Praneet Thakur (B19CSE066) and Priyansh (B19CSE067)
Team Name- Team Sklearn

Abstract

These days when the effects of the global pandemic are getting worse,it is very important that people should wear face masks whenever they are in public places.So a technological construct for detecting whether a person has worn face masks or not is indeed very important. The purpose of this project is to gain a deeper understanding of different classification models, and how they perform on the mask nomask dataset. As for the approach, we will implement various machine learning models(Multilayer Perceptron,Convolution Neural Network,Random forest,Adaboost,K Nearest neighbours) on the original dataset.

Index Terms

Face mask detection, convolution, multilayer perceptron, boosting

I. Introduction

Image classification is one of the most fundamental problems in Machine Learning. It is the core foundation for bigger problems such as Computer Vision, Face Recognition System, or Self-driving car. With the development of deep Convolutional Neural Network (CNN), researchers have achieved good performance on the image recognition task.We would use the mask nomask dataset for the task of image classification between people who have worn mask or not. We will compare the performance of CNN with classic machine learning models: MLP (Multilayer Perceptron), Random Forest, K Nearest Neighbors, Boosting. We would analyse which model gives the best results and what can be the possible reasons for the same.

Hypothesis: We expected that due to the famous and recognised ability of CNN to analyse and recognise patterns it would do better than most of the algorithms, and we also expected that MLP would be performing better than others but not better than CNN because of the added convolutional layers. And also we can't really judge models just like that, there might be a few cases where the least expected model could outperform others but that all depends on the hyperparameters of the models.

II. Dataset

Figure below shows the sample images from the dataset used.

Fig. 1. Mask No-Mask dataset sample images

III. System Design and Methodology

This section describes the models and methodology used in this project. We first create two image generators i.e one for testing images and the corresponding labels and other for validation images and the labels. We resclae the pixel values of the images suvh that each pixel ranges from 0 to 1. The inage generates batches of images.We have used the following models in our project to provide a comparitive analysis and to determine which model has dominance.
(1) MLP (Multilayer Perceptron) We generate a MLP model from keras. There are three hidden layers in the model one with 2050,1030,510 neurons each layer has a dropout layer of 0.2 in between.The optimizer used is adam and relu is used for

activation. We have used the number of epochs as three.
(2) Random Forest- It uses sklearn library.
(3) CNN-This model also uses keras library. Firstly there is a convolution network with three (3 cross 3) conv layers each layer has a maxpool (2*2) abd filters are different for each layer.There are three dense layers in the model one with 1024,64,32 neurons each layer has a dropout layer of 0.2 in between.The optimiser used is adam and relu and softmax are used for activation. We have taken the number of epochs as five but more could be taken depending on time availability.
(4) KNN-It stands for K nearest neighbors. Here, we used KNN from sklearn library. We have used the numbers of nearest neighbors to be taken in count as 10.
(5)Adaboost- This is another ensemble learning technique that we have used for this dataset. Adaboost is a sequential technique. Its a model that learns from the incorrect classifications that it has done by changing their weights in the next iteration. I have used the numbers of estimators to be 100 in this case.

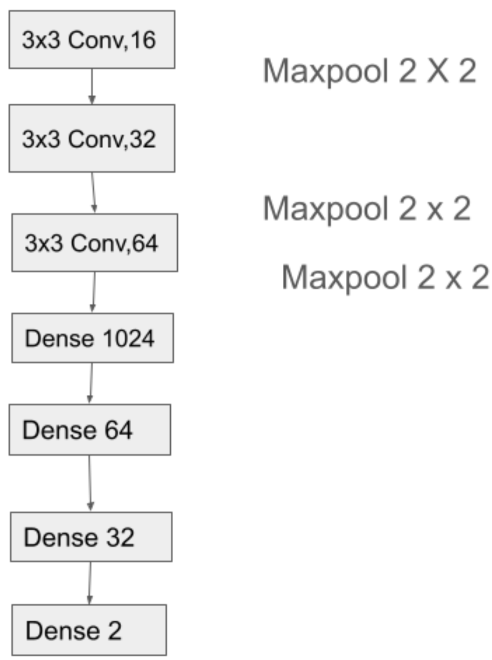

Fig. 2. Deep CNN model architecture

IV. Experiment and Analysis

This section summarises the results of the experiments and detailed analysis of each approach. To compare the performance of each model, the accuracy is used and cross validation scores is used.

A. *Scores for different models*

The following table represents the accuracies and the cross validation scores for the models used.
All values in percentage.

Model	Accuracy	Cross-validation scores
MLP	73.95	78.125, 78.125, 65.625
CNN	89.53	90.62, 84.375, 93.75
Random forest	60.47	56.12, 65, 60.31
Adaboost	59.35	51.31, 55.43, 71.31
KNN	42.08	43.56, 44.62, 38.06

This Table summaries the experimental results for the baseline approach. The best model in this approach is CNN model, with an 89.53 percent accuracy for mask nomask dataset.

The possible reasons that we could think for the disparity in the accuracies are basically that each model has a different background implementation and different mathematical formulation. Therefore we can't really expect each algorithm to have perform similar to others. And also there might be some particular cases when each of them similarly but that would mainly depend on how we have tweaked with the hyperparameters of the models.
The following figures shows the graphical comparison between the models.
In fig.1, the models have been compared on the basis of their accuracy percentages. Fig.2 compares the models on the basis of their cross-validation scores And later in fig.3, we can see the outputs we got for each of the models in our code.

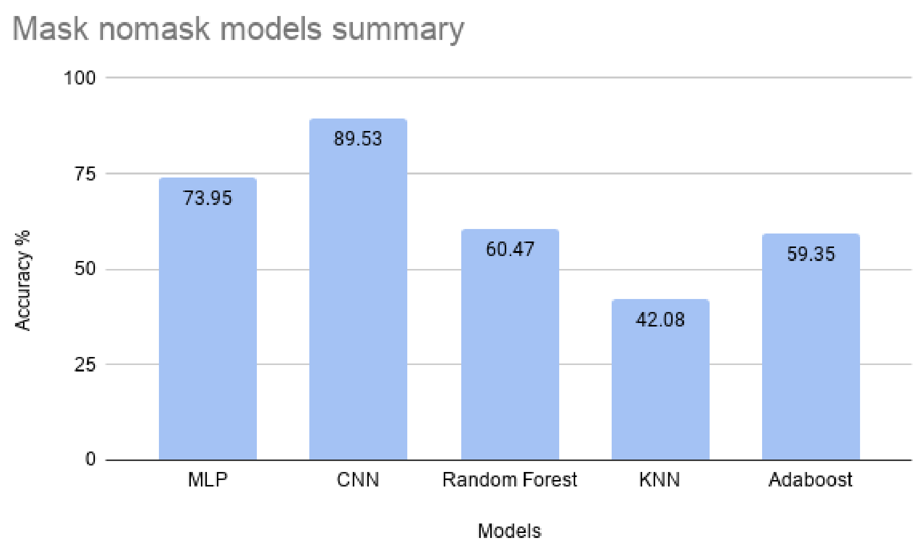

Fig. 3. Mask no-mask models summary

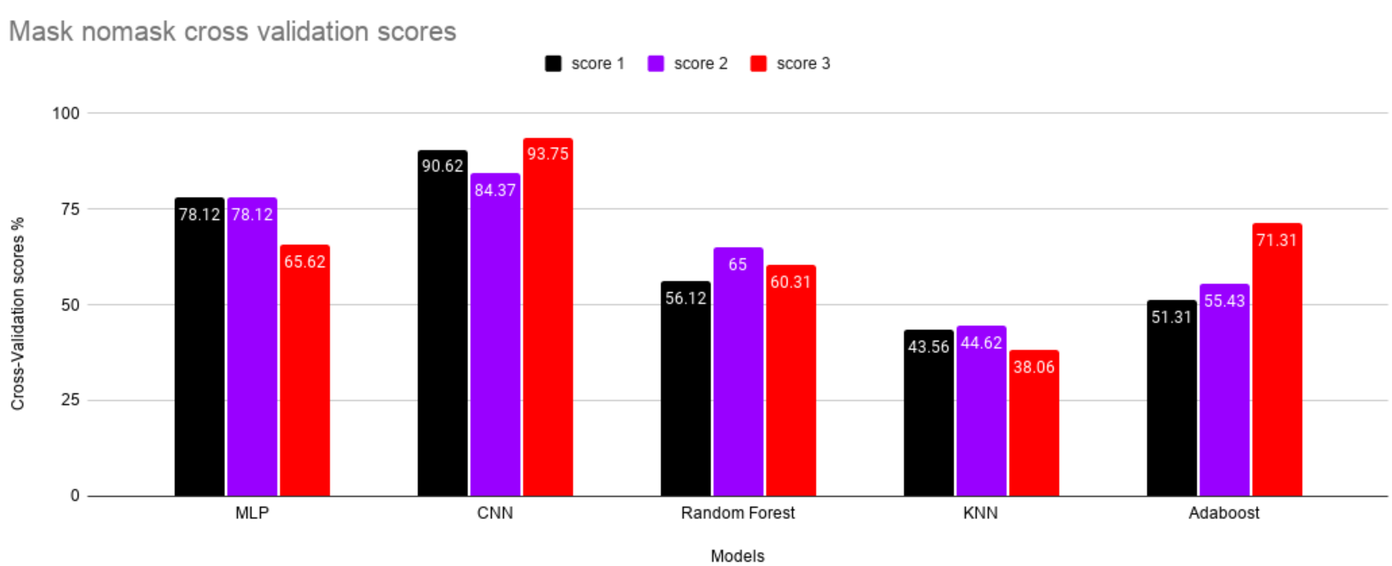

Fig. 4. Cross validation scores comparison

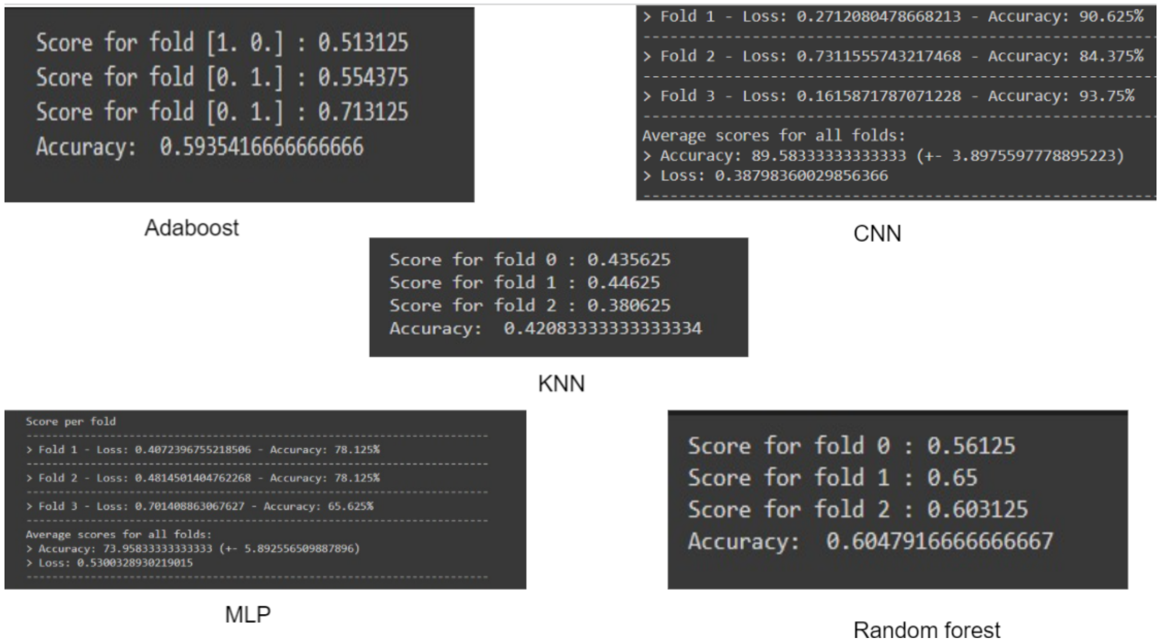

Fig. 5. Outputs for all the models

V. Conclusion

We have used a number of models to train for the mask nomask dataset. Out of which it can be easily seen that CNN outperforms all the others by giving a higher accuracy of 89.53 percent, followed by MLP then the ensemble algorithms are performing almost equally, the KNN gives the lowest accuracy. From this it can be easily concluded that the convolutional neural networks due to its ability to recognise patterns in images outshines all the other models.

A. Reasons for choice of models

We mainly chose the implemented models because we wanted to show the dominance that the convolutional networks have in the field of computer vision and pattern recognition. Also we have chosen the models because we wanted to compare a diverse range of models having different functional back grounds. We chose some ensemble learning methods like Adaboost and Random forest, we also chose a distance classifying algorithm like KNN and deep learning models i.e MLP and CNN which altogether has different and unique approach as compared to others.

As expected CNN outperforms all the other models. And also as said that mlp would be doing better than other models but not better than CNN proved to be a valid point.

VI. Contribution

Research and planning- Praneet and Priyansh
Coding-Praneet and Priyansh
Image generation- Priyansh
Random Forest- Praneet
Knn- Praneet
Adaboost- Praneet
MLP- Priyansh
CNN-Priyansh

Report- Praneet and Priyansh

REFERENCES

[1] https://keras.io/api/models/sequential/
https://keras.io/api/layers/convolution$_{l}ayers/convolution2d/$
$https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html$
$https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.AdaBoostClassifier.html$
$https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html$
$https://keras.io/api/preprocessing/image/$