FaceMask Detection

Shivam Sharma *(B19CSE084)*, Shubh Doshi *(B19EE080)*

Abstract

This paper implements and compares different classifiers and machine learning techniques which have been used to determine whether a person is wearing a face-mask or not.

I. Introduction

IN this paper, we contain a dataset containing pictures of two types, faces with masks and without masks. We attempt to train different models on said images and compare which model is better at predicting if a person is wearing a mask or not. We also train a CNN (Convolutional Neural Network) for the same.

II. Preprocessing

Dataset was uploaded to google drive and was included from there. Our dataset has 2203 with mask images and 4500 without mask images. All the images were then converted to gray scale. Then the images were resized to (64 x 64) and flatten to extract all the pixel values(features). The dataset was then randomly shuffled such that the whole dataset consists of randomnly spread images of people with mask and without mask.

III. Dimensionality Reduction

The training and testing dataset is then standardized for applying dimensionality reduction techniques LDA and PCA to reduce the feature dimensions.

A. Scaling

The dataset is standardized using StandardScaler.

B. PCA

Principal Component Analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets. Hence, PCA was applied here on the dataset of 6703 images, reduced dimensions being stored in appropriate variables.

C. LDA

Linear discriminant analysis (LDA) is a dimensionality reduction technique reduces the feature dimensions by minimizing the intraclass distances and maximizing the distances between different classes. LDA is applied on the whole dataseta and the transformed dimensions are aptly stored.

IV. Training

This section describes the training of 3 different models namely- ***SVC, MLP and Random Forest***. Each of the 3 models are trained on 3 different datasets namely- ***original, PCA transformed and LDA transformed***.

A. Normal Dataset

Metric	SVC	MLP	Random Forest
Accuracy	0.943	0.689	0.922
F1 Score	0.905	0.512	0.867
Log Loss	1.956	10.757	2.676

B. PCA Transformed Dataset

Metric	SVC	MLP	Random Forest
Accuracy	0.933	0.921	0.870
F1 Score	0.894	0.878	0.786
Log Loss	2.316	2.728	4.478

C. LDA Transformed Dataset

Metric	SVC	MLP	Random Forest
Accuracy	0.979	0.981	0.979
F1 Score	0.967	0.969	0.967
Log Loss	0.720	0.669	0.720

V. CNN

A. MobileNetV2

MobileNetV2 is a convolutional neural network architecture that seeks to perform well on mobile devices. It is based on an inverted residual structure where the residual connections are between the bottleneck layers.
Its hyperparameters were varied and were finally decided as follows:
1) Learning Rate: 1e-4
2) Epochs: 20
3) Batch Size = 32
One hot encoding was performed on the labels and the data was then split into training and testing. Few additions were made to the base model MobileNetV2 after which it was fitted on the data.
After the model was fitted, the model predicted classes for test data and the prediction accuracy came to be 0.873. A graph has also been plotted containing training and validation's loss and accuracy.

VI. Graphs

Cross - validation for different datasets and different classifiers was carried out and was plotted on a boxplot for comparison. (Graphs are available at the bottom of the document)

VII. Conclusion

Thus, we conclude that Classifier SVC works better on the normal as well as the PCA transformed dataset while MLP get the best result in LDA transformed data.

The **maximum accuracy** was achieved by classifier **MLP** using the **LDA transformed** dataset.
We observe that that all the classifier work better on LDA transformed dataset as compared to the other datasets.This happens due to the size of the dataset. PCA works better when there are less number of samples per class, however since we only have 2 classes and have a large dataset, models don't work as well on PCA transformed dataset. However large size is a boon for LDA, thus the 3 models perform their best on LDA transformed dataset.

The ensembling of CNNs could have been better applied by hypertuning the parameters in a better way to increase the accuracy.

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References

[1] https://scikit-learn.org/stable/
[2] https://keras.io/

VIII. Contribution

A. ***Shubh Doshi***

Contributed in gathering and extracting the images of the dataset and also in preprocessing the dataset. Applied the dimensionality reduction technique LDA which efficiently helped in reducing the features and has achieved the highest score in the project compared to other datasets. Also, performed the SVC classifier training, testing and comparison by analysing the results of reduced-data/original-data and plotted the results. Conceived to use the idea of CNNs and also implemented and analysed the MobileNetV2 Version of CNN, by hypertuning it and changing layers in addition to it.

B. ***Shivam Sharma***

Contributed in preprocessing the dataset and extracting features by converting image to gray scale and resizing them to 64*64 size.Implemented shuffling of the dataset which reduces any bias during training and helps it to converge faster. Implemented PCA dimensionality reduction technique which reduced the number of features significantly and achieved better accuracy as compared to normal dataset. Analysed the results of different datasets on MLP and Random Forest Classifiers and plotted the results. Also contributed in implementing MobileNetV2 Version of CNN and varying hyperparameters accordingly.

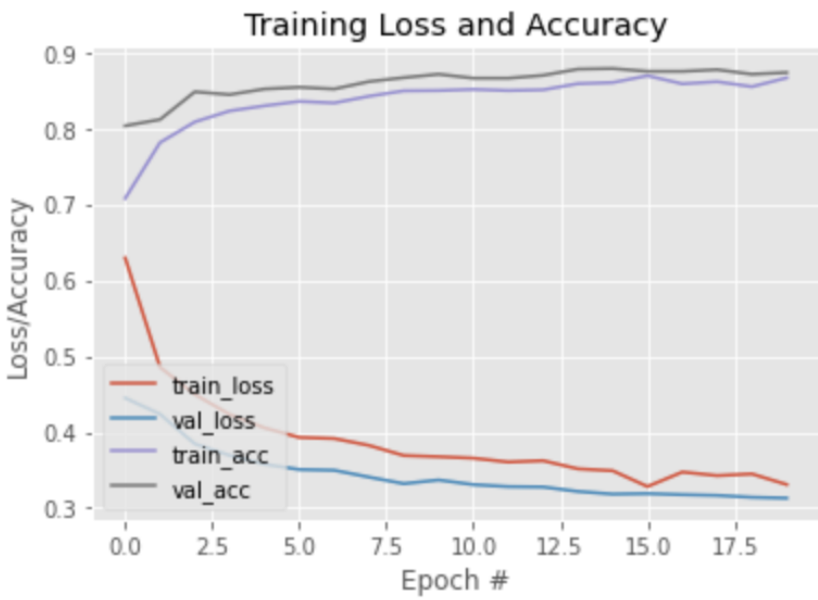

Fig. 1. CNN

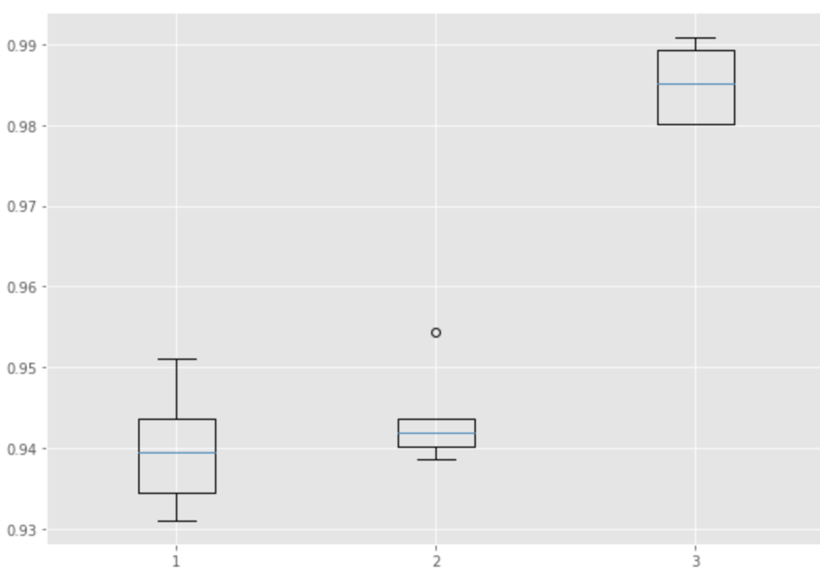

Fig. 2. SVC: 1-Normal, 2-PCA transformed, 3-LDA Transformed

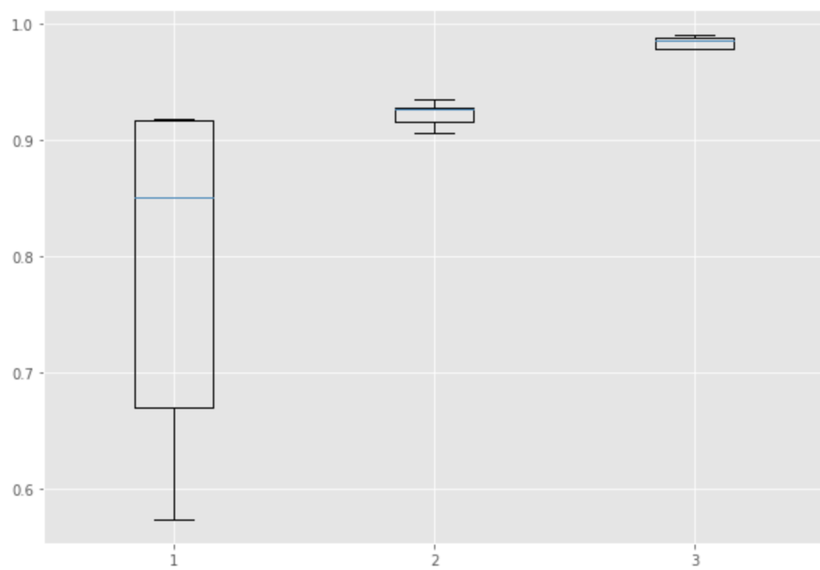

Fig. 3. MLP: 1-Normal, 2-PCA transformed, 3-LDA Transformed

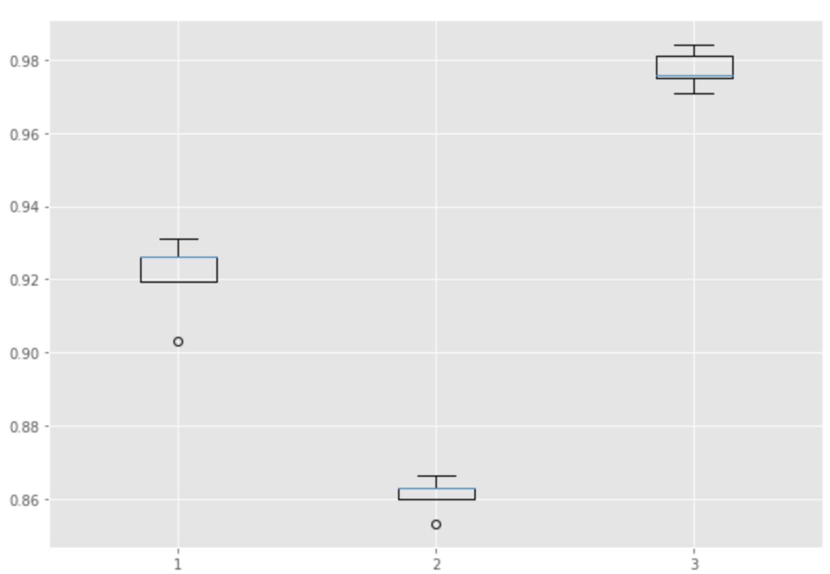

Fig. 4. Random Forest: 1-Normal, 2-PCA transformed, 3-LDA Transformed