

Face Mask Detection Using MobileNet

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Abstract: COVID-19 virus is a pandemic that affects the whole world. It is a viral disease that affects almost everyone in one way or another. However, the effect will be different depending on many factors. The global pandemic has affected education and commerce around the world. Many people lose their lives, work, etc. Wearing a mask has become the norm. In the future, COVID-19 will spread very quickly. Everyone needs to wear a mask to avoid this. Therefore, the quest for facial recognition has become an important task to help the world. This article describes the findings of two types of people wearing and not wearing masks. To solve these problems, an automated facial recognition system using machine learning algorithms has effectively managed the spread of COVID-19. We propose a MobileNet-based architecture to detect image descriptions of inappropriate facial expressions. It turned out that someone who was not wearing a mask was detected and a warning was sent. If they do not wear a mask at that time, a fine is sent.

Keywords: Machine Learning, Python, MobileNet.

1. Introduction

A. General

Face mask detection has become an important topic in recent times due to the COVID-19 pandemic. The use of face masks is an effective way to prevent the spread of the virus, and many countries have made it mandatory to wear masks in public places. However, enforcing these regulations can be challenging, and face mask detection technology has emerged as a promising solution.

In this context, MobileNetV2, a state-of-the-art deep neural network architecture designed for mobile and embedded devices, can be a powerful tool for face mask detection. MobileNetV2 is particularly well-suited for this task because it is optimized for efficiency and can run on low-power devices such as smartphones and embedded systems.

B. Machine Learning

Machine learning is self-learning without programming, with an emphasis on developing algorithms. Python is a popular programming language for developing machine learning applications due to its ease of use, large number of libraries and tools, and active community. Machine learning is one of the most exciting technologies mankind has encountered. As the name suggests, it gives computers the ability to become human – the ability to learn. Machine learning is used today in more areas than you might expect.

C. MobileNetV2

MobileNetV2 is a state-of-the-art deep neural network architecture designed for mobile devices and graphics. The main innovation of MobileNetV2 is the use of a new technique called "linear bottleneck layer" that improves the efficiency and accuracy of the network. These layers use a combination of 1x1 convolutions and 3x3 deep convolutions to reduce the number of parameters in the network without precision.

D. Image

A collection of four-sided box pixels (picture components) an image is made up of rows and columns. An artefact, such a two-dimensional picture, that closely resembles a subject—typically a genuine object or a real person—is called an image (from the Latin *imago*).

E. Image Processing

Image processing is any type of signal processing where the input is an image, such as a photograph or video frame, and the output is either an image or a collection of properties or features related to images. The majority of image-processing techniques include processing the image according to basic signal-processing principles and treating it as a dimensional signal.

In figure 1, an (8-bit) greyscale image has picture elements with intensity values ranging from 0 to 255. Similar to a black-and-white image, a greyscale image emphasizes that it will also contain different shades of grey.

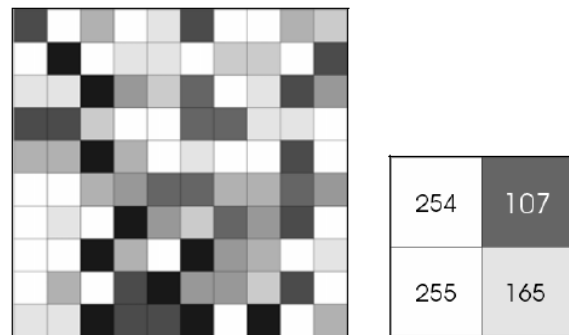


Fig. 1. Different shades of grey

F. Image Enhancement

Image enhancement is the process of increasing the clarity of digital photographs without knowing what caused the

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degradation (for example, for machine analysis or visual examination). Image restoration is the method used when the cause of the degradation is found. Both processes use images as their input and output, making them both ironical.

2. Existing System

Existing papers have explored the use of Deep Neural Networks (DNNs) for face mask detection. However, DNNs typically rely on many fully-connected layers and suffer from several drawbacks, including being a black box, requiring significant development time, needing a large amount of data, and being computationally expensive. Moreover, DNNs may not be efficient in detecting the correct faces and can have low accuracy. Additionally, the use of DNNs in IoT models can result in exponentially high hardware costs. Overall, while DNNs have been used for face mask detection, there are several challenges that need to be addressed to improve their efficiency and accuracy.

A. Drawbacks

- DNNs require a large amount of training data to achieve high levels of accuracy. In the case of face mask detection, this can be particularly challenging, as the number of face mask images available for training may be limited.
- DNNs require significant computational resources, which can be expensive and slow down the detection process. This can be problematic in real-time applications where fast detection is crucial.
- The use of DNNs for face mask detection can result in high hardware costs, especially in IoT models where processing power and memory capacity may be limited.

3. Proposed System

The proposed work is focused on developing a system to detect whether a person is wearing a face mask or not. The COVID-19 pandemic has highlighted the importance of wearing face masks to prevent the spread of the virus, and this system can play a vital role in enforcing mask-wearing policies in public places. To achieve this goal, the proposed system uses MobileNetV2, a state-of-the-art deep neural network architecture, to accurately detect a person's face in an input image or video frame. MobileNetV2 is particularly well-suited for this task as it is optimized for efficiency and can run on low-power embedded systems.

Overall, the proposed system provides an efficient and accurate solution for detecting whether a person is wearing a face mask or not. This can be especially useful in public places such as schools, offices, and hospitals, where mask-wearing policies need to be strictly enforced. The system can help to reduce the spread of the virus and protect public health.

A. Architectural Design

The proposed method focuses on providing a system for detecting face masks that is both efficient and accurate. The public's safety will be improved as a result of this method.

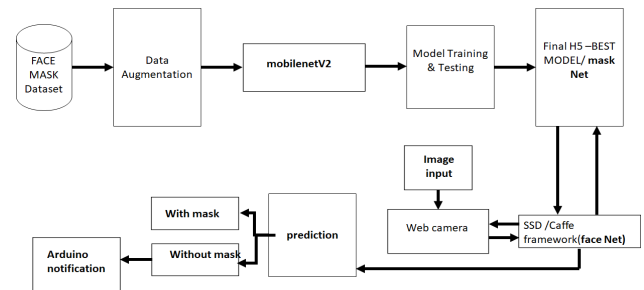


Fig. 2. Overall architecture

B. Modules

1) Data Collection

Determine the number of images or videos required for the dataset, the resolution of the images or videos, and the minimum number of faces to be included in each image or video. Collect data from a variety of sources, such as public databases, social media platforms, or online videos. Ensure that the data is diverse and representative of different ethnicities, genders, ages, and facial expressions.

- 1915 images, which consists of people wearing face masks.
- 1918 images which consists of people not wearing face mask.

2) Data Pre-processing

Creates an instance of Image Data Generator from the Keras library. It sets a number of parameters to apply data augmentation to the training images, including random rotation within a range of 20 degrees, random zoom within a range of 0.15, random shifts in width and height within a range of 0.2, random shear within a range of 0.15, and random horizontal flipping.

3) Model Training

MobileNetV2 is a deep convolutional neural network architecture designed for real-time object detection and classification. The architecture uses depthwise separable convolutions to reduce the number of parameters and computation costs, while maintaining high accuracy. The network uses residual connections, to allow gradients to flow more easily through the network, and a linear bottleneck layer to reduce computation costs.

4) Model Testing

Classification Accuracy: Classification Accuracy is what we usually mean, when we use the term accuracy. It is the ratio of number of correct predictions to the total number of input samples. It works well only if there are equal number of samples belonging to each class.

5) Prediction

Performs face mask detection in real-time using a webcam video stream. We use two deep learning models: one for face detection and one for face mask classification. The face detection model is the Single Shot MultiBox Detector (SSD) trained on the Caffe framework, while the face mask classification model is a MobileNetV2 network trained using TensorFlow/Keras. We use OpenCV for video streaming and pre-processing of the images, and TensorFlow/Keras for predictions.

4. Output

The proposed approach aims to improve the performance of the face mask recognition system. The dataset collected is from different sources like Kaggle and Google.

Here we analyse masked, non-masked and partial masked images this process is done in data partitioning to provide best results the model is trained with equal number of masked and non-masked images so the best results are provided in both cases.

The data is partitioned in the ratio of 80: 20 where 80% is used training and 20% is used for testing.

Table 1
Data partitioning

Data	Partition Data
Training	80%
Testing	20%

Table 2
Algorithm outcomes

Algorithm	Accuracy	Loss
MobileNetV2	.99	.022

```

C:\Windows\System32\cmd.exe
114s 910s/step - loss: 0.3119 - accuracy: 0.8700 - val_loss: 0.0886 - val_accuracy: 0.9727
Epoch 2/20
115s 1s/step - loss: 0.0578 - accuracy: 0.9678 - val_loss: 0.0543 - val_accuracy: 0.9822
Epoch 3/20
126s 1s/step - loss: 0.0607 - accuracy: 0.9783 - val_loss: 0.0386 - val_accuracy: 0.9827
Epoch 4/20
113s 950s/step - loss: 0.0560 - accuracy: 0.9818 - val_loss: 0.0372 - val_accuracy: 0.9895
Epoch 5/20
113s 900s/step - loss: 0.0465 - accuracy: 0.9847 - val_loss: 0.0315 - val_accuracy: 0.9937
Epoch 6/20
116s 950s/step - loss: 0.0398 - accuracy: 0.9871 - val_loss: 0.0302 - val_accuracy: 0.9927
Epoch 7/20
113s 950s/step - loss: 0.0334 - accuracy: 0.9884 - val_loss: 0.0278 - val_accuracy: 0.9927
Epoch 8/20
113s 950s/step - loss: 0.0314 - accuracy: 0.9902 - val_loss: 0.0274 - val_accuracy: 0.9927
Epoch 9/20
113s 950s/step - loss: 0.0317 - accuracy: 0.9905 - val_loss: 0.0262 - val_accuracy: 0.9916
Epoch 10/20
114s 950s/step - loss: 0.0290 - accuracy: 0.9892 - val_loss: 0.0247 - val_accuracy: 0.9937
Epoch 11/20
115s 950s/step - loss: 0.0241 - accuracy: 0.9921 - val_loss: 0.0245 - val_accuracy: 0.9927
Epoch 12/20
115s 960s/step - loss: 0.0234 - accuracy: 0.9918 - val_loss: 0.0239 - val_accuracy: 0.9937
Epoch 13/20
115s 950s/step - loss: 0.0271 - accuracy: 0.9918 - val_loss: 0.0233 - val_accuracy: 0.9948
Epoch 14/20
115s 970s/step - loss: 0.0220 - accuracy: 0.9931 - val_loss: 0.0235 - val_accuracy: 0.9927
Epoch 15/20
114s 960s/step - loss: 0.0216 - accuracy: 0.9934 - val_loss: 0.0243 - val_accuracy: 0.9927
Epoch 16/20
120s 1s/step - loss: 0.0259 - accuracy: 0.9918 - val_loss: 0.0216 - val_accuracy: 0.9937
Epoch 17/20
116s 970s/step - loss: 0.0214 - accuracy: 0.9929 - val_loss: 0.0262 - val_accuracy: 0.9916
Epoch 18/20
113s 950s/step - loss: 0.0185 - accuracy: 0.9950 - val_loss: 0.0219 - val_accuracy: 0.9948
Epoch 19/20
113s 950s/step - loss: 0.0173 - accuracy: 0.9939 - val_loss: 0.0200 - val_accuracy: 0.9937
Epoch 20/20
113s 940s/step - loss: 0.0133 - accuracy: 0.9952 - val_loss: 0.0222 - val_accuracy: 0.9948
1100] evaluating network...
    
```

Fig. 3. Epochs training

```

[INFO] evaluating network...
      precision    recall  f1-score   support

with_mask      0.99      1.00      0.99      383
without_mask   1.00      0.99      1.00      571

 accuracy
macro avg      0.99      1.00      0.99      954
weighted avg   0.99      0.99      0.99      954

[INFO] saving mask_detector_model...
    
```

Fig. 4. Training accuracy and Loss percentage

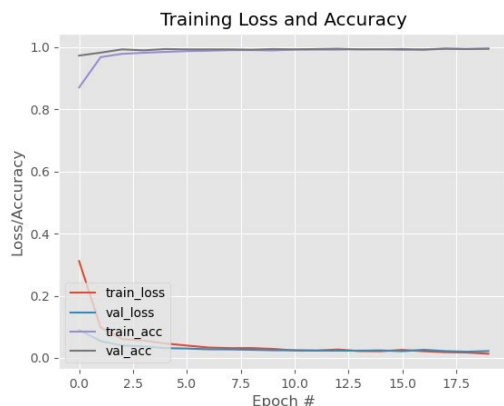


Fig. 5. Training accuracy and Loss graph plot

5. Conclusion

In conclusion, the use of deep learning algorithms such as MobileNetV2 has shown great potential in the field of face mask detection, particularly in the context of the ongoing COVID-19 pandemic. The proposed face mask detection system using MobileNetV2 provides an whether a person is wearing a face mask or not in real-time. Efficient and accurate way to detect.

Face mask detection is an important application of computer vision that has become increasingly relevant in the context of the COVID-19 pandemic. MobileNetV2 can be a good choice for face mask detection, as it is a lightweight and efficient neural network architecture that can run on mobile devices and in real-time applications.

When using MobileNetV2 for face mask detection, it is important to consider the specific requirements of the task and the dataset. The quality and size of the dataset will play a critical role in the accuracy and generalization ability of the model. It is important to ensure that the dataset is diverse and representative of the target population, and that it includes enough examples of each class (mask, no mask, incorrectly worn mask) to enable the model to learn meaningful features

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