IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Detect Face Mask Wear By People Using Machine Learning

Riya Kumari[*1], Dr. Kamalraj R[*2]

[*1] MCA, Department of MCA, Jain University Bangalore, India,

[*2] Associate Professor, Department of MCA, Jain University Bangalore, India

Abstract: COVID-19 virus has serious consequences Emergency affecting the health of most people Being in most parts of the world Greater effect by affecting people's health. Important Effective methods are established by maintaining social distance And the duty of the mask. Above all, wearing a mask reduces the risk of getting the disease. We try to present a mix model with a classic model Machine learning algorithms, deep learning recognition. The dataset may or may not have images. A mask that attempts to use OpenCV for real-time detection on a webcam. Because it is essential Wear a face mask in public areas for added safety People, we make sure that such a system is implemented for security and for security reasons. You can also use the same model in a workplace that promises that all employees wear masks During the day. Create using a dataset COVID 19 face mask detector using computer vision, Tensor Flow, Python, Keras. Our main goal is to identify whether a person has a face in an image / video stream whether to mask deep learning. We provide a Machine Learning-based system for detecting improper use of face masks. Our system uses Convolutional Neural Network (CNN) architecture with two stages that can recognize both masked and unmasked faces and is compatible with pre-installed CCTV cameras. This will be aid in the tracking of safety contravention, the promotion of face mask use, and the creation of a safe working environment.

Keywords: Machine learning, face mask, CNN, MobileNet V2.1.

1. Introduction

COVID-19 virus is presently affecting the complete world. To manipulate the clarify of the Corona virus; humans are utilising loads of strategies. There are severa vital precautions that have to be taken to fight COVID-19, one of the maximum extensive of that's the usage of a face masks. COVID19 continues to be the focus of much research and research. Wearing a face masks has additionally been proven to unusually reduce the hassle of infections in studies. Present confirmation suggests that the virus spreads mainly between people who are in close contact with each other, for example at a conversational distance. The virus can spread from an infected person's mouth or nose in small liquid particles when they cough, sneeze, speak, sing or breathe. When infectious particles in the air are inhaled at close range (this is known as short-range aerosol or short-range airborne transmission) or when infectious particles come into direct contact with the eyes, nose, or mouth droplet transmission, another person can get the virus.

The performance of modern computer vision algorithms in visual perception tests is approaching that of humans. Computer Vision has shown to be a game-changing feature of current technology, from image categorization to video analytics. Technology has proven to be a lifesaver in the fight against the pandemic of Novel Coronavirus Disease (COVID-19). Work-from-home has become a part of our daily lives as a result of technological advancements. However, for some industries, adapting to this new norm is impossible. Individuals are still wary of returning to work as the pandemic settles and such sectors become more willing to restart in-person labour. Sixty-five percent of workers are dreading going back to work..

1.1. Traditional Object Detection: The problem of detecting multiple masked and unmasked faces in images can be solved by a traditional object detection model. The process of object detection mostly involves localizing the objects in images and classifying them (in case of multiple objects). Traditional algorithms like Hear Cascade have proved to be current for such tasks, but these algorithms are heavily constructed on Feature Engineering.

A CNN uses convolution kernels to convolve with the original images or feature plans to extract higher-level features, so resulting in a very powerful tool for Computer Vision tasks.

1.1.1. Modern Object Detection Algorithms: CNN based object detection algorithms can be classified into 2 categories: Multi-Stage Detectors and Single-Stage Detectors. Multi-Stage Detectors In a multi-stage detector, the process of detection is splitting into multiple steps. A two stage detector like RCNN first estimates and proposes a set of regions of interest using selective search. The CNN feature vectors are then removed from each region independently. Multiple algorithms based on Regional Proposal Network like Fast RCNN and Faster RCNN have achieved higher accuracy and better results than most single stage detectors.

Single-Stage Detectors A single-stage detector performs detections in one step, directly completed a dense sampling of possible locations. These algorithms skip the region suggestion stage used in multi-stage detectors and are thus considered to be generally faster, at the cost of some loss of accuracy. One of the most popular single stage algorithms, You Only Look Once (YOLO), achieved close to real time performance. Single Shot Detector (SSD) is alternative popular algorithm used for object detection, which gives excellent results. Retina Net one of the best detectors, is built on Feature Pyramid Networks uses focal loss.

1.1.2. Face Mask Detection: against the Coronavirus, numerous implementations of Face Mask Detection systems came forth. Require performed facial recognition on masked and unmasked faces using Principal Component Analysis (PCA). Though, the recognition accuracy drops to less than 70% when the accepted face is masked.

They distributed the facemask wearing conditions into three categories: correct face mask wearing, incorrect face mask wearing, and no face mask wearing. Their system takes an image, detects and crops faces, and then uses SrcNet to perform image super-resolution and classify them. a process that detects the presence or absence of a medical mask. The primary objective of this method was to trigger an alert only for medical staff who do not wear a surgical mask, by decreasing as many false positive face detections as possible, without missing any medical mask detections. Proposed a model that consists of two components. The first component performs uses ResNet50 for feature extraction. The next component is a facemask classifier, based on a group of classical Machine Learning algorithms.

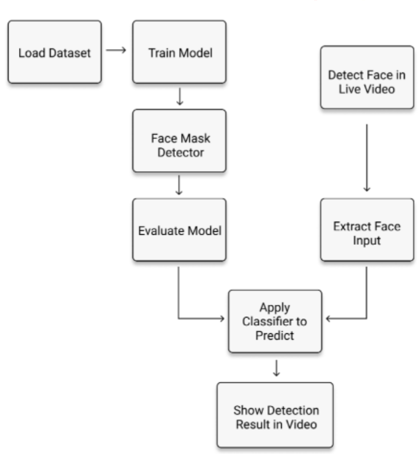


Fig. Facemask detection

1.1.3. Proposed Methodology: We propose a two-stage construction for detecting masked and unmasked faces and localizing them.

It consists of two main phases. The first stage of our architecture consist of a Face Detector, which localizes multiple faces in images of changing sizes and detects faces even in overlapping scenarios. The detected faces (sections of interest) extracted from this stage are then batched together and accepted to the second stage of our architecture, which is a CNN based Face Mask Classifier. The results from the second stage are interpreted and the final output is the image with all the faces in the image correctly detected and classified as each masked or unmasked faces.

A face detector actions as the first stage of our system. A raw RGB image is accepted as the input to this stage. The face detector removes and outputs all the faces detected in the image with their bounding box coordinates. The process of detecting faces correctly is very important for our architecture. Training a highly correct face detector needs a lot of labelled data, time, and compute resources. For these aims, we selected a pre-trained model trained on a large dataset for easy generalization and stability in detection. Three different pre-trained models were tested for this stage Dib - The Dib Machine Learning face detector offers significantly better performance than its precursor, the Dib HOG based face detector.

MTCNN - It uses cascade architecture with three stages of CNN for detecting and localizing faces and facial key points. It is a single stage proposal with pixel-wise localization that uses a multi-task learning strategy to simultaneously predict face box, face score, and facial key points. The detection process is testing for the model used in this stage, as it needs to detect human faces that could also be covered with masks.

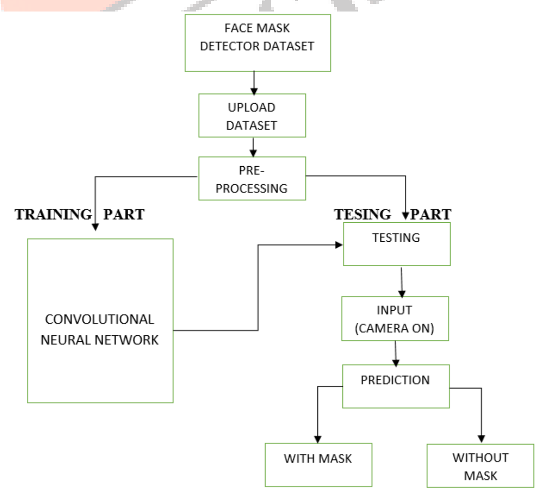


Fig. Proposed Methodology

1.1.4. Intermediate Processing Block: This block carries out the processing of the distinguished faces and groups them together for classifier, which is carried out by Stage 2. The detector from Stage 1 outputs the bouncing boxes for the faces. Stage 2 requires the complete head of the person to accurately classify the faces as masked or unmasked.

The first step includes expanding the bounding boxes in height and width by 20%, which covers the required Section of Interest (ROI) with minimal overlap with other faces in best conditions. The second step involves cropping out the expanded bouncing boxes from the image to extract the ROI for each detected face. The extracted faces are resized and normalized as mandatory by Stage 2. Furthermore, all the faces are batched together for batch inference.

1.1.5. Stage 2 - Face Mask Classifier: The second stage of the system is the face mask classifier. This stage takes the processed ROI from the In-between Processing Block and classifies it as either Mask or No Mask. A CNN founded classifier for this stage was trained, based on three different image classification models: MobileNetV2 , DenseNet121 . These models have a lightweight engineering that offers high performance with low latency, which is suitable for video analysis.

The output of this phase is an image (or video frame) with a localized face classified as a masked or unmasked face.

1.1.6. Dataset: Three face mask classification models were trained on the dataset. Masked and unmasked face dataset images were collected from publicly available image datasets, along with data retrieved from the Internet. Veiled pictures were gotten from This present reality Concealed Face Acknowledgment Dataset (RMFRD) Face Mask Detection dataset by Laurel on Cagle .

Fig. Dataset

1.1.7. Final Results: Consolidating every one of the parts of our engineering, we thus get a highly accurate and robust Face Mask Detection System. Retina Face was selected as our Face Detector in Stage 1, while the NASNetMobile based model was selected as our Face Mask Classifier in Stage 2.The resulting system is high performance and can detect face masks in multiface images over a wide range of angles.

1.1.8. Video Analysis: As of recently, we have seen that our framework shows elite execution over pictures, defeating a large portion of the issues normally looked in object location in pictures. In real-world scenarios, it would be beneficial to extend such a detection system so that it also works with video feeds. Video has its own challenges such as motion blur, dynamic focus, and transitions between frames. We used an object tracking process to stabilize the detection and avoid jitter between frames. We used a modified version of histogram pursuing, to follow the recognized countenances between continuous casings. This makes our recognition calculation hearty to the commotion and the movement obscure in video streams, where the algorithm could fail to detect some objects.

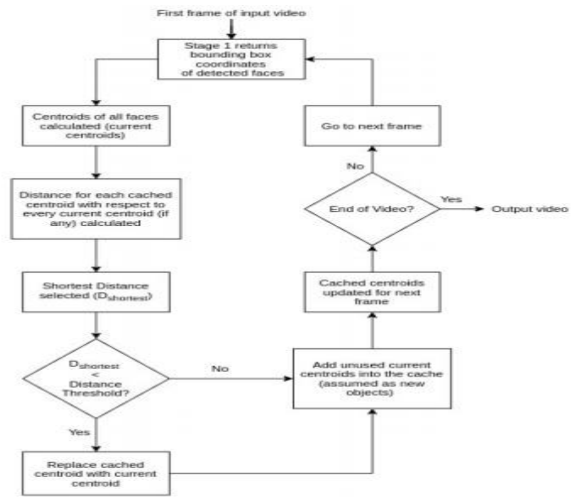


Fig. Video Analysis

The detected face ROIs in a given frame are tracked over a predefined number of edges so that the The ROI coordinates of the face are preserved even if the detector does not recognize the object during the transition between frames. We chose five edges as the limit in 30 FPS video transfers for disposing of the reserved centroids, which gave great outcomes with the most un-bogus positive face location in video streams. After using this method, there was a important improvement in face mask detection in video streams. The following results show the difference in detection with and without histogram Following:

1. Machine Learning Classifiers:

These are used to are expecting the class/labels/classes of a given records points. Classification belongs to the class of supervised studying wherein the goals are furnished with enter records. They are used in lots of packages like clinical diagnosis, unsolicited mail detection, goal advertising and marketing etc. They use a mapping function (f) from enter variables (X) to discrete output variables(Y).

2.1.Opencv:

OpenCV is an open-supply library that is in general used for Computer Vision Applications. This incorporates many features and algorithms for Motion tracking, Facial reputation, Object Detection, Segmentation and reputation and plenty of different packages. Images and actual time video streams may be manipulated to fit distinct desires the usage of this library.

1.2. Tensorflow:

It is an open-supply device studying framework to construct and teach neural networks. It has a group of tools, libraries and network sources which enables in clean constructing of deployment of ML powered packages. The entire sequential CNN architecture (composed of multiple layers) uses TensorFlow on the backend. It is also used to reshape data (images) in data processing.

1.3. Keras

Keras presents the basic considerations and components for building and transferring ML arrays at high speeds. Get the most out of Tensor Flow scalability and cross-platform capabilities. All layers used in the CNN model are implemented in Keras. Not only is it useful for data processing to convert class vectors to binary class matrices, but it is also useful for building the entire model.

1.4. Computer Vision:

It is a field that involves processing, interpreting, and comprehending high-dimensional data from the actual world in order to generate numeric and symbolic.

2. Aim Of The Project:

Face masks (or other face covering that cover your mouth and nose) are one of the most effective measures that help reduce spreading of the virus. The face cover helps prevent the spread of the virus by blocking respiratory droplets containing virus particles.

• Help us take the necessary safety measures by predicting the future outbreak of COVID-19 (new coronavirus infection).

• Provide a safe working environment.

• Save lives.

3. Related Works:

Dalai, N., and Trigs, B. the work done in this project Semantic Segmentation Detection of Facial Masks In image processing and computer vision, face detection has become a popular problem. To make the algorithm as accurate as feasible, many new methods are being designed employing convolutional architectures [1].

Deng, J., Dong, W .the work done in this project Even pixel information can now be extracted thanks to these convolutional designs. The goal is to create a binary face classifier that can recognize any face in the frame, regardless of its alignment. We show how to make accurate face segmentation masks from any image of any size. For feature extraction, the method starts with an RGB image of any size and employs VGG – 16 Architecture Predefined Training Weights. To semantically separate out the faces present in the image, Fully Convolutional Networks are used for training. The training function is Gradient Descent, while the loss function is Binomial Cross Entropy. Furthermore, the FCN's output image is processed to remove undesired noise, avoid any incorrect predictions, and create a bounding box around the faces. In addition, the suggested model has demonstrated excellent performance in the recognition of non-frontal faces. It can also recognize several masks on the face in a single shot. The segmented face masks achieved a mean pixel level accuracy of 93.884 percent in experiments using the Multi Parsing Human Dataset.
Facial Masks and Neural Networks for Face Recognition One of the most fascinating biometric modalities [2]

Deng, J., Guo, J., Ververas, E., Kotsia, I., and Zafeiriou, S. the work done this project is face recognition. It's ideal for a wide range of real-time applications because of its low intrusiveness and the constant decrease in image acquisition costs. The inclusion of a linearly shaded elliptical mask cantered over the faces in this research proposes a very quick picture pre-processing. It can be used in conjunction with DCT for feature extraction and MPL and RBF Neural Networks for classification to improve system performance while reducing learning time for MLP neural networks. Improved Mask R-CNN Based Face Detection and Segmentation Face detection has recently proven effective using Machine convolutional neural networks [3].

Despite their development, most existing detection systems only use a bounding box to locate each face, which makes it impossible to segment each face from the background image at the same time. To address this shortcoming, we propose G-Mask, a face recognition and segmentation method based on enhanced Mask R-CNN that combines face detection and segmentation into a single framework with the goal of obtaining more fine-grained face information. ResNet-101 is used to extract features, RPN is used to produce Roils, and Roiling reliably retains the exact spatial coordinates to construct binary mask by Fully Convolution Network (FCN). Furthermore, the bounding box loss function is Generalized Intersection over Union (Giroux) to improve detection accuracy. On the FDDB, AFW, and WIDER FACE benchmarks, the suggested G-Mask approach has shown promising results when compared to Faster R-CNN, Mask R-CNN, and Multitask Cascade CNN [4].

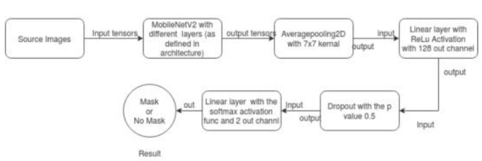
Facemask Net is used to identify face masks in real time. Network of Machine Learning The COVID - 19 pandemic is wreaking havoc on humanity, regardless of caste, creed, gender, or religion. We should all do our part to limit the corona-spread virus's until a vaccine is discovered. The use of a face mask can surely aid in the control of the virus's spread. The use of a face mask will surely aid in the control of the virus's spread. The use of a face mask will surely aid in the control of the virus's spread. Facemask net, Machine learning algorithms are used or owned by COVID - 19 face mask detector to successfully evaluate whether or not a person is wearing a face mask. Person wearing a mask, incorrectly worn masks, and no mask found are the three classifications presented in the manuscript. We achieved an accuracy of 98.6 percent using our Machine learning algorithm called Facemask net. Facemask works for both still images and live video broadcasts. When the nose and mouth are partially covered by the mask, this is considered improper use. It is deemed improper to wear a mask that partially covers the nose and mouth. Our face mask identifier has the simplest structure and produces quick results, so it may be used in CCTV footage to determine whether a person is correctly wearing a mask and so poses no threat to others. In busy venues such as train stations, bus stops, markets, streets, mall entrances, schools, colleges, and so on, mass screening is practicable and so can be deployed. We can ensure that an individual wears the face mask correctly and thereby helps to limit the virus's spread by monitoring how the mask is placed on the face. In the age of the COVID-19 pandemic, a hybrid Machine transfer learning model combined with machine learning approaches for face mask detection [5].

The epidemic of the coronavirus COVID-19 is wreaking havoc on the world's health. Wearing a face mask in public places, according to the World Health Organization, is one of the most effective protection techniques (WHO). Face mask detection will be discussed in this paper using a hybrid model that combines Machine and traditional machine learning. Two components make up the suggested model. The first component employs Resnet50 to extract features. The second component uses decision trees, Support Vector Machines (SVM), and an ensemble method to classify face masks. For this study, three face-masked datasets were chosen. The Real-World Masked Face Dataset (RMFD), the Simulated Masked Face Dataset (SMFD), and the Labelled Faces in the Wild are the three datasets (LFW). In RMFD, the SVM classifier has a testing accuracy of 99.64 percent. It scored 99.49 Percentage test accuracy with SMFD and 100% test accuracy with LFW. COVID-19 face mask detection using machine learning and computer vision [6].

4. Methodology

Proposed system:

During pandemic COVID-19, WHO has made wearing masks compulsory to protect against this deadly virus, so our project will notify if someone is wearing mask or not. In this project, we will develop Machine learning. Using Python, Opens, Tensor Flow, and Keas, we will leverage the dataset to create a COVID-19 face mask detector with computer vision. Our goal is to use computer vision and Machine learning to determine whether or not the individual in the image/video stream is wearing a face mask.



MobileNetV2 architecture: MobileNetV2 is an architecture of bottleneck depth separable convolution building of basic blocks with residuals. It has two types of blocks as shown in Fig. 1. Both blocks have three layers. The first one is 1x1 convolutions with "ReLU6". The second layer contains depth-wise "convolution," and the third layer contains a 1x1 "convolution" with no non-linearity. The first layer is a one stride residual block. As seen in Table 1, the second layer is also a residual block with stride 2 and is used for shrinking. The methodology of object detection is to make a classification to determine the input class, regression to adjust the bounding box. With the exception of the last completely connected layers, most backbone webs for detection are networks for classification tasks. The backbone network serves as a simple feature extractor for object detection tasks, taking images as input and producing feature maps for each input image.

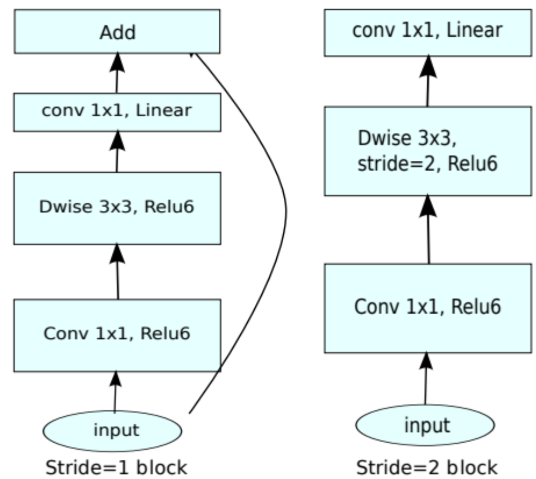


Fig. MobileNetV2 blocks

Advantages:

- High Accuracy.
- Losing rate reduces.
- Time minimising.

Training and Loss Accuracy:

The training step is very important for the model to find the weights that best accurately represent the input data to match its accurate output class. Thus, these weights are continuously updated and moved towards their optimal output class. In this study, we trained a CNN model using a face mask detection dataset. During the training process, the training data was divided into 100 small batches. Batch size divides the entire dataset into a chain of reduced datasets and feeds them into the model one at a time. Dividing the training dataset into batches helps to train the model faster and control the accuracy of gradient errors. Likewise, the learning rate of 0.001 Used to set the size of the step to minimize the loss functions. The optimization algorithm, forward pass, loss function, backward pass, and weights updates are followed to train the model from the labeled data.

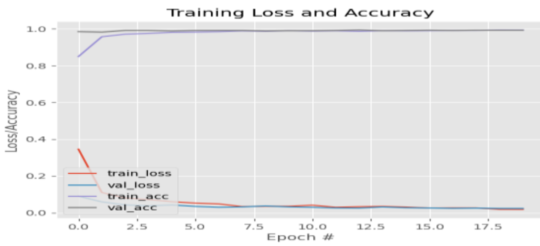


Fig. Training And Loss Accuracy

5. Implementation:

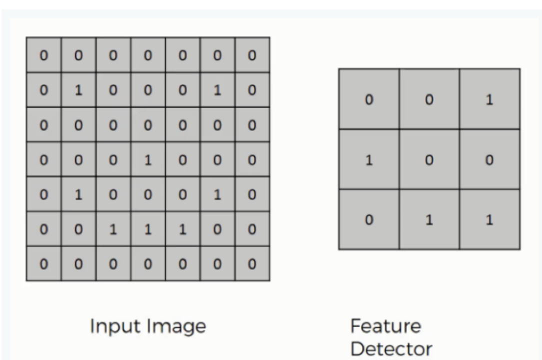
The architectural design is the design process for identifying the subsystems making up the system and framework for subsystem control and communication. The goal of the architectural design is to establish the overall structure of software system as shown below.

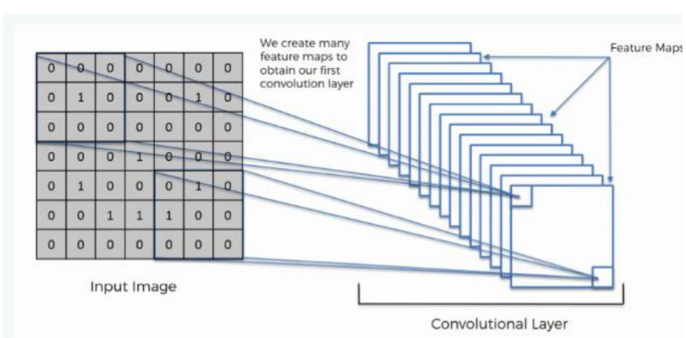
Convolutional Neural Network

Step1: convolutional operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. it also describes feature maps and learns the parameters of such maps, how patterns are perceived, the level of recognition, and how the results are mapped.

The Convolution Operation



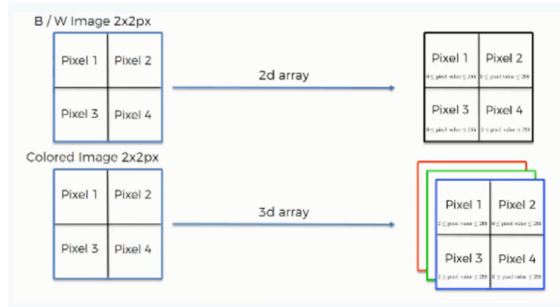


Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills.

Convolutional Neural Networks Scan Images



Step 2: Pooling Layer

In this part, we'll cover pooling and will get to understand exactly how it generally works. However, the nexus here is a kind of pooling. Maximum pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part ends with a demonstration created with a visual interactive tool. This ensures that the entire concept is cleared.

Step 3: Flattening

This may be a short breakdown of the knocking down manner and the way we circulate from pooled to flattened layers while operating with Convolutional Neural Networks.

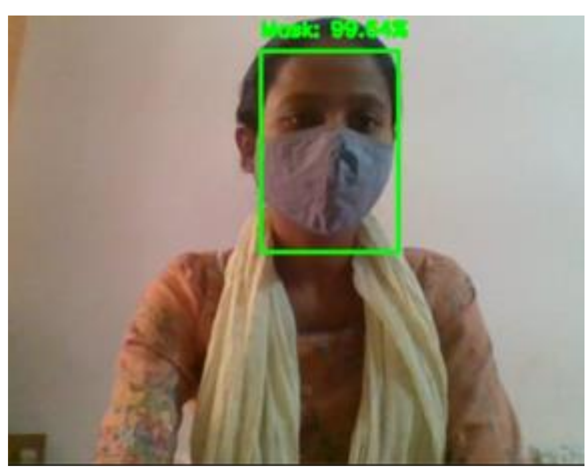
Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

6. Results and Discussions

Our project is about a person is captured with mask or without mask. The results are given as below:

With mask:



When a person is captured with wearing mask. Then our project gives the result as shown as the above picture.

Without mask:

When a person is captured without wearing mask. Then our project gives the result as shown as the above picture.

6. Future Scope

The model proposed here provides high accuracy for individual faces with or without masks. It also provides very good accuracy for multiple surfaces. Simply turn on the video stream without the need for external hardware and it will work seamlessly on any mobile device. Further we will work for improving the accuracy for multiple face mask detection, to classify the faces in to three categories that is, With mask, without mask, In proper mask instead of just the two with and without mask class by adding datasets with images of people wearing masks not covering their noses properly and also to detect the masked face using the Face Net model of CNN.

7. Conclusion

In this application, a two-stage Face Mask Detector was presented. The first stage uses a pretrained caffe model for robust face detection, after comparing its performance with Dib and CNN. An unbiased dataset of masked and unmasked faces has been created. The second stage involved training three different lightweight on the basis of performance, the deploy PROTOTX-based Face Mask Classifier model was chosen for categorising faces as masked or non-masked. Furthermore, centroid tracking has been added to the algorithm to improve performance in video streams. In the era of the COVID 19 pandemic, this system can be easily used for automatic monitoring of face mask use in the workplace when people are resuming their personal work in the hope that the world will return to normal, which will help make them safer.

References

1. Dalai, N., and Trigs, B., Histograms of oriented gradients for human detection, CVPR '05, 2005.
2. ImageNet: A Large-Scale Hierarchical Image Database, IEEE Computer Vision and Pattern Recognition (CVPR), 2009. Deng, J., Dong, W., Soccer, R., Li, L.-J., Li, K., and Fei-Fei, L.
3. Deng, J., Guo, J., Ververas, E., Kotsia, I., and Zafeiriou, S., Retina Face: Single-Shot Multi-Level Face Localisation in the Wild, 2020,
4. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA, 2020, pp. 5202-5211, doi: 10.1109/CVPR42600.2020.00525.
5. Dong, C., Loy, C.C., Tang, X., Accelerating the Super-Resolution Convolutional Neural Network, in Proceedings of European Conference on Computer Vision (ECCV), 2016.
6. Implementation of principal component analysis on masked and non-masked face recognition, 1st International Conference on Advances in Science, Engineering, and Robotics Technology (ICASERT), 2019, Ejaz, M.S., Islam, M.R., Sifatullah, M., and Sarker, A.
7. 1–5. Rich feature hierarchies for accurate object detection and semantic segmentation, Girshick, R., Donahue, J., Darrell, T., and Malik, J., Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2014,
8. Fast R-CNN, Proceedings of the IEEE International Conference on Computer Vision, 2015, pp. 1440–1448. 8. Girshick, R., Fast R-CNN, Proceedings of the IEEE International Conference on Computer Vision, 2015.
9. Glorot, X., and Bengio, Y., Understanding the difficulty of training Machine feedforward neural networks, Proceedings of the 13th International Conference on Artificial Intelligence and Statistics (AISTATS).
10. Machine residual learning for image recognition, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770– 778. 10. He, K., Zhang, X., Ren, S., and Sun, J.,
11. Howard, J., Huang, A., Li, Z., Tufekci, Z., Zdimal, V., van der Westhuizen, H., von Delft, A., Price, A., Fridman, L., Tang, L., Tang, V., Watson, G.L., Bax, C.E., Shaikh, R., Questier, F., Hernandez, D., Chu, L.F., Ramirez, C.M., Rimoin, A.W., Face Masks Against COVID-19: An Evidence Review. Preprints 2020, 2020040203, (doi: 10.20944/preprints202004.0203.v1).
12. Huang, G., Liu, Z., Van Der Maaten, L., and Weinberger, K. Q., Densely Connected Convolutional Networks, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 2261-2269,
13. T., Laine, S., and Aila, T., A Style Based Generator Architecture for Generative Adversarial Networks, 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, 2019.
14. LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P., Gradient-Based Learning Applied to Document

Recognition, Proceedings of the IEEE, 86(11):2278-2324, November 1998.

15. Lin, T., Dollár, P., Girshick, R., He, K., Hariharan, B., and Belongie, S.J., Feature pyramid networks for object detection, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), vol. 1, no. 2, 2017a, p. 4.
16. Lin, T., Goyal, P., Girshick, R., He, K., and Dollár, P., Focal Loss for Dense Object Detection, 2017 IEEE International Conference on Computer Vision (ICCV), Venice, 2017b, pp. 2999-3007, doi: 10.1109/ICCV.2017.324.
17. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., and Berg, A.C., SSD: Single shot multibox detector, European Conference on Computer Vision, Springer, 2016, pp. 21–37.
18. Loey, M., Manogaran, G., Taha, M. H. N., & Khalifa, N. E. M. (2021) (in press), A hybrid Machine transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic, Measurement: Journal of the International Measurement Confederation, 167.