RESEARCH ARTICLE OPEN ACCESS

Face mask detection model based on deep CNN technique using AWS

Ritesh Tandon
Department of Data Science
Protective Life
Birmingham, AL, USA

Aniqa Sayed
School of Public Health
University of Alabama at Birmingham
Birmingham, AL, USA

Muhammad Anas Hashmi
Environmental& RM
BTU Cottbus-Senftenberg
Wolfratshausen, Germany

Date of Submission: 25-04-2023 Date of acceptance: 05-05-2023

Abstract—Since the outbreak of the epidemic coronavirus infection (COVID-19) in Wuhan, it's become a public health concern in China, and subsequently globally. That pandemic consumes wreaking havoc upon the world's cultures and economics. This extremely large number of COVID-19 samples provides valuable information regarding the pandemic's progression, as well as a possible way to encircle it to prevent future transfers. To reduce the spread of the virus, several prophylactic methods have been introduced, and one is the usage of a mask. Wearing a face mask that limits the transmission of droplets discharged into the atmosphere, on either hand, may help avoid the outbreak. As a solution, the goal of this work will be to create a Face Mask Detection model which can be used as part of an embedded imaging system. That model was trained to use a dataset that includes images of people wearing a mask but without the mask that was acquired through Kaggle and GitHub. At first, these collected face mask image datasets have merged and preprocessed in that it consisted following steps image reshaping, normalization, and data augmentation. After image preprocessing of this dataset, the deep MTCNN model has been used to make the Face Mask Detection model in our framework. People who do not use masks have been identified. It is expected to enhance the detection rate and achieve an accuracy of more than 99%. Python was used to construct the system, while AWS was used to execute it. This project has presented a comparative evaluation of existing face detection and faces mask classification methods. As a result, this system may monitor persons wearing or whether there will still be a breach inside the scenario or even in open places, without wearing masks inside a smart city in real-time. It is expected that our research will serve as a model for many nations throughout the world to prevent the transmission of this deadly virus. This has been utilized in conjunction with the current embedding camera network to provide these insights that have been employed in a variety of disciplines such as in-office towers or at airport depots.

Keywords— Face Mask Detection (FMD), COVID-19, deep learning, CNN,

I. INTRODUCTION

The process of recognizing whether someone is wearing a mask is known as face mask detection (FMD). It is one of the non-pharmaceutical strategies that may be employed to reduce a principal source of COVID droplets ejected by an infected person. Wearing a mask is an example of this. This project seeks to develop an extremely precise & real-time system that can easily identify non-mask faces in public as well as, as a result, compel people to wear masks to contribute to the improvement of community health. Even though many academics are focused considerable efforts on inventing successful approaches for image recognition, there seems to be a significant difference between 'detecting of the face underneath a mask' with 'recognition of the mask across the face.' Facial recognition seems to be a reversed manufactured issue in which a person's face gets recognized utilizing different machine learning methods for security, validation, and surveillance purposes; in fact, the challenge has been known as reverse engineering with face detection. When it comes to Computer Image processing and pattern recognition, face detection is a critical range of study. In the past, a considerable amount of research has led to the growth of advanced processes for face identification. The first face detection study was carried out in 2001, and it included the development of handicraft features and the use of typical ML methods to train efficient classifiers for the identification & detection of human faces. The difficulties met by this method comprise a high level of difficulty in feature strategy as well as a low level of accuracy in detection. ML is the investigation of computational models that learn and develop autonomously because of its interactions with the world. In the area of AI, it is considered a subset of ML techniques to construct a precise model using sample data to create predictions or choices without having been expressly taught to do so. Email filtering and computer visi[2on are only a few examples of areas where machine learning algorithms are being employed since developing traditional algorithms to fulfill the required tasks is difficult or impossible. A tight relationship exists between machine learning and computational statistics, which both concentrate on generating predictions using computers. [1].

II. RELATED WORK

[2] During this research, a method was developed to identify the usage of masks in face photographs. To train the Convolutional Neural Network, they used a dataset of 11,740 face photos. The system will be aided in object categorization and identification with the assistance of CNN. VGG-16 is the exact model used in this system. Researchers apply the Augmentation Technique in the preprocessing step in the belief that it would provide excellent results and aid in the epidemic. It does have the maximum training accuracy of 99 %, as well as the best validation accuracy of 99 % as well as a strong, give accurate information outcome.

[3] In this research, they describe a method that suppresses COVID-19 generation by detecting persons who do not use face masks inside a smart city network in which all public venues were monitored via Video cameras. Authorities are alerted via the city's network whenever an unmasked individual appears. All the photos of individuals, either with or without masks from different sources, are used to train a deep learning approach. For previously undiscovered test data, the trained architecture correctly distinguished between persons wearing and not wearing an FM with an accuracy of 98.7 percent.

[4] The proposed deep learning technique for creating face masks from any size picture is both precise and efficient. The approach leverages VGG - 16 Platform's Predefined Training Weights for feature extraction from any RGB picture of any size. Aside from that, the suggested model has performed very well when it comes to recognizing faces that are not frontal. Besides this, it is also capable of detecting numerous face masks in the same picture. Tests on the Multi Parsing Human Dataset yielded 93.884 percent accuracy for the segmented mask faces.

Likewise, with this study [5] a method for detecting the usage of masks in face photographs has been developed and tested. A collection of 11,740 facial photos is gathered and fed into the CNN, which then learns from the data. The system will be supported in the procedure of object categorization & recognition with the assistance of CNN. In this system, researchers are using the VGG-16 model, which is a unique model. For the preprocessing step, researchers use the Augmentation Technique to improve the outcomes, with the goal that it will provide positive results and would be of assistance in the fight against the pandemic. Ultimately, it produces the best results for training accuracy (100 percent) and validation accuracy (99 percent), as well as a respectable result for test accuracy (90 percent).

In this work [6], The FR-TSVM model, as well as the transfers learning method, are used to investigate the most recent stats on the pneumonia epidemic state in Covid-19 using the most current available information. The first step was to acquire a data set of 12,000 face photographs taken in public while wearing masks and without masks for purpose. The photographs will be included in the revised VGG model. After that, the structure of the VGG model was utilized to extract the characteristics of photographs. These characteristics were learned using the FR-TSVM with fuzzy ideas incorporated. This strategy has the potential to attain 95.5 percent accuracy, which is greater than the detection results obtained by previous approaches.

In this work, [7] primary emphasis will be on artificial intelligence algorithms for masked face identification and associated datasets. They begin with images of mask face detection and recognition databases and work their way up to some of the most recent advancements. The information which has now available is thorough and thoroughly researched. In the next section, the approaches are essentially divided into two categories: traditional approaches and NN-based techniques. Predictable techniques are often taught using boosting processes with hand-crafted features, then account for just a tiny share of all training methods in use today. The machine-learning techniques have been further classified under 3 types depending on the number of processing stages required. Several sample algorithms were detailed, as well as several conventional techniques which are simply explored. Finally, they provide a summary of current benchmarking findings, as well as reflections on the limits of datasets and methodology, as well as suggestions for future research initiatives. That is the best of our data, and this is the first survey of masked face recognition algorithms & datasets to have been conducted. Perhaps, the results of our survey will be useful in the battle against diseases.

According to [8], using a face mask to guard against airborne infectious illnesses, including COVID-19, is among the most ways of protecting oneself. Because of the widespread COVID-19, affected nations have implemented rigorous mask regulations for those who work or visit public places inside their homes or companies. The use of a face mask is mandatory; nevertheless, the position & kind of mask must be examined to maximize the efficacy of face masks, particularly in certain public places. Conventional face recognition technology, on the other hand, finds it difficult to distinguish between persons for security cheques. DL techniques are presented to construct a complete mask recognition system using a camera to address this challenge. Each scenario's characteristics are classified using a Deep Learning model such as CNN, AlexNet, and VGG16, as well as Facial Recognition Pipeline with FaceNet, which are all named CNN, AlexNet, as well as VGG16, respectively. A variety of available datasets, Google Image Search, including simulated photographs, are used in this research.

In this research work, [9]are going to see the serious technological application of computer technologies in the disciplines of artificial intelligence & ML, with a particular emphasis on CV and IP. Approaches like ours are frequently used to detect real-world objects, e.g., human faces and other facial features. As a result, they can distinguish a person from a photograph by using such approaches. Designers can train techniques to identify individuals even though they are wearing masks by using image recognition modules from the vast array of Python libraries available. Because half of a person's facial characteristics are gone when a mask is worn, creating a strategy to detect faces in this manner is essential. Face detection is a specialized technique that is used in biometrics, video surveillance, and other applications. Consequently, it is critical to boost both the security and efficiency of identification while also speeding up the recognition process.

In this work, [10] offer a method for recognizing face masks in videos using deep learning. To identify faces, including their related facial landmarks in an image sequence, the suggested framework makes use of the MTCNN face identification model developed by Microsoft. Those images and cues were examined via one neoteric classifier that employs the MobileNetV2 structure as a detection algorithm and detects masked regions which can then be utilized to identify individuals. To validate the proposed framework, it was applied to a dataset consisting of films documenting the movement of individuals in public areas while adhering to COVID-19 safety guidelines. When it comes to identifying face masks, the suggested technique has shown to be useful by reaching high precision, recall, and accuracy.

In this work,[11] identify persons who are not wearing a face mask in an SCN in which all the public locations are recorded thru CCTV cameras and implement a method to boundary spread COVID-19 in a smart city network. When a person without the need for a mask is spotted, the proper authorities are notified via the city network's communications system. To train a deep neural network model, it is necessary to use a dataset that contains photographs of individuals with and without masks that have been obtained from different sources. For recently declassified test data, the trained infrastructure obtained an accuracy of 98.7 percent when it came to identifying between those wearing & not wearing FMD. Several nations across the globe are hoping that our research will prove to be an effective tool in slowing down the development of this contagious illness.

III. PROBLEM IDENTIFICATION

Countless people have lost their lives, and there are now serious security concerns because of COVID-19. People often use masks to protect themselves from the coronavirus and limit its spread. Given that some features of the face are concealed, facial identification becomes very challenging. Coronavirus pandemic experts are working hard to come up with quick and effective ways to combat the disease. An old computer vision issue has been the detection of faces. Face masking has several drawbacks, not the least of which is to avoid detection; fraudsters and criminals use the mask to steal and conduct crimes. Community access control & face authentication have become extremely challenging jobs when most of the user's face is concealed behind a mask. Recognizing someone is very difficult if you can't see their face because of a face mask. A restricted number of variations makes it difficult for deep-learning models to learn. Therefore, the solution to the problem of restricted data availability may lie in over-sampling. Presently, the face mask recognition algorithm fails to identify people wearing masks with their faces covered by their hands. Multiple faces can't be detected at the same time by the system. For the time being, the system only recognizes a single face mask. In densely crowded areas, this method fails miserably.

IV. PROPOSED METHODOLOGY

The exceptionally high number of COVID-19 samples provides further information about the pandemic and may help us encircle it to stop future transmissions. Masks are one of several infection-prevention methods. This research develops an embedded imaging system for Face Mask Detection (FMD). We propose identifying people without face masks in a smart city network where CCTV cameras monitor all public spaces to prevent COVID-19 spread. Deep learning creates an MT-CNN model. This model was trained using Kaggle and GitHub pictures of mask-wearing and mask-free persons. These image datasets were merged and pre-processed by reshaping in (196*196) and normalizing. MTCNN created the Face Mask after image pre-processing. MTCNN is widely used for deep learning. Detection is in our framework. Python and AWS deployed it. This project compared face detection and mask classification algorithms. So, this system can monitor mask-wearers and non-mask-wearers in smart cities in real-time if there is a scenario or public space violation.

4.1. Dataset Collection

A dataset is built by combining images from numerous sources. This is used to train as well as test the model [12][13]; researchers gathered information from two distinct sources. We have 858 photos of individuals wearing masks and 681 photos of people who aren't wearing masks. Pictures from 80 percent of each class are used for training, while images from the remaining 20 percent are used for testing.

4.2. Image Pre-processing

Various preprocessing techniques & image segmentation are employed to enhance the input image & emphasize the foreground elements. Before moving on to the next phase, the pictures acquired by the CCTV cameras needed to be preprocessed. For face mask identification, RGB color images contain too much redundant data. Thus, the picture is converted into a grayscale image in the pre-processing stage. Each pixel of an RGB color picture has 24 bits of data. The grayscale picture, on the other hand, retained 8 bits of information for every pixel and could be used for categorization. We next restructure the photos into (64x64) shapes to keep the architecture consistent with the input images. When the pictures have been normalized, a pixel's value falls anywhere between 0 & 1. The learning system was able to pick up more information from the photos quicker, thanks to normalization.

4.3 Data Normalization

Pre-processing is a fundamental part of data mining that involves standardizing data. In other words, changing the data or translating the original data into a format that can be processed successfully. The primary goal of data normalization is to reduce or eliminate the amount of redundant information.

V. DEEP LEARNING

Deep Learning has improved discriminative tasks. Complex network architecture, powerful processing, and easy access to enormous data quantities cause this. CNN advancements may aid computer vision applications like image categorization, object identification, and image segmentation. These neural networks preserve visual spatiality with sparsely connected kernels. Convolutional layers diminish picture resolution while increasing feature map depth. Convolutional transforms can simplify visual representations. CNN's achievement has piqued interest in Deep Learning for computer vision applications. [14].

5.1 Adam optimizer

Adam optimizer has been used in the proposed model. Adam is a mathematical formula for finding the best possible solution to a problem. The weights of the network are repeatedly updated depending on the training data using the Adam optimizer. If you need to train a network on huge datasets, Adam is a good option since it is simple to construct, computationally efficient, and requires just a modest amount of memory.

5.2Loss Function: Binary_Crossentropy

The loss function measures how much the algorithm's current output differs from what it is predicted to produce. According to the usual binary cross-entropy loss function [15]:

$$j_{bce} = -\frac{1}{M}\sum_{m=1}^{M}[y_m \times \log(h_\theta(x_m)) + (1 - y_m) \times \log(1 - h_\theta(x_m))]$$

M: number of training examples
y_m:target label for training examples m
x_m:input for training examples m
h_θ:model with neutral network weights

VI. RESULTS

The suggested system is evaluated in a python simulation environment and compared to current approaches. Face mask identification has crucial for image analysis, computer vision, identification, or confirmation. Photos with and without masks are included on the recommended system's training dataset, and the system has been processed, and augmented, with attributes retrieved or categorized. Using the suggested deep learning based MTCNN model, the proposed system's mask identification accuracy is compared to the current CNN model. Training and testing/validation sets are created by maintaining an acceptable percentage of distinct classes in the face mask dataset. The dataset contains 1539 samples, of which 90% are utilized for training, and 10% are used for testing/validation. In the training and testing/validation datasets, there are 1231 and 308 pictures. Since extended training leads to overfitting of the training data, the built architecture is only trained for 20 epochs. An overfitting problem happens when a model picks up on patterns in the training data that it doesn't need to learn. As a result, training accuracy improves, but test accuracy decreases. Various scenarios with a constant number of epochs and batch size of 32 were run through the model, and the results are summarized in the table below. Experimenting using a variety of variables, python libraries, and deep-leavening modeling frameworks. In addition to the graphs shown in Fig. 1 and Table 1, the accuracy and loss graphs are also shown.

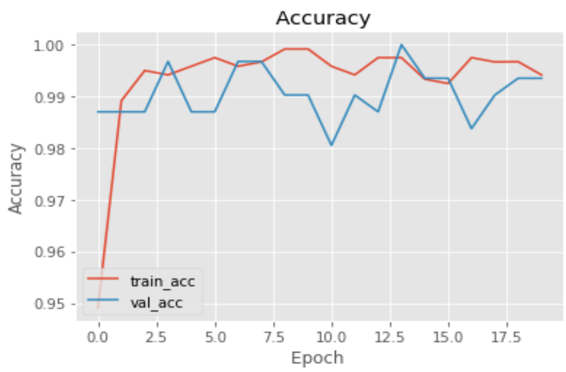

Figure 1: Accuracy of the developed system for the training and validation phase

The training and validation accuracy curves are displayed in Figure.1 for about 20 epochs. The training and validation accuracy is almost comparable, as shown in Figure1 As a result, the model has a good capacity for generalization and does not overfit its training data.

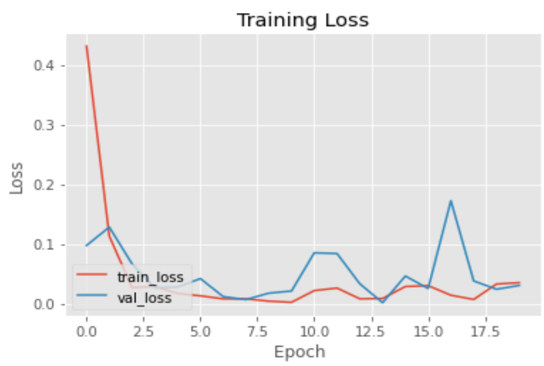

Figure 2: Loss of the developed system for the training and validation phase

Figure 2 shows the training and validation losses curve. 2. As the number of epochs rises, the training error reduces. Over time, the validation loss began to outweigh the training loss, indicating that the accuracy of the prediction was deteriorating. During the 19th period of validation, the validation loss is within an acceptable range.

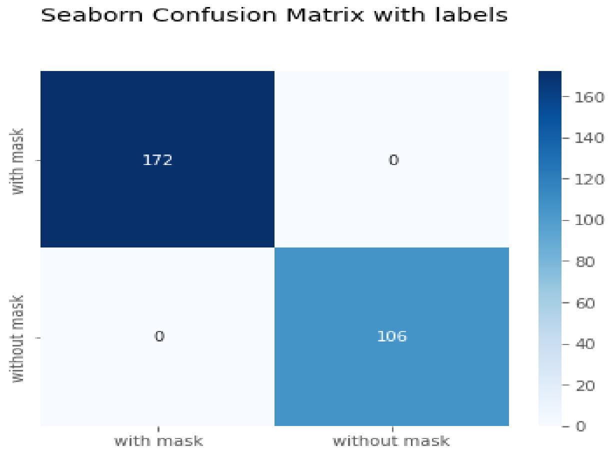

Figure 3: Confusion matrix of the proposed MTCNN model

The testing phase's confusion matrix is shown in Figure 3. This confusion matrix is developed using the Python seaborn library. There are only 0 misclassifications out of 308 samples in the developed architecture. There are no samples in this class that have a mask.

	precision	recall	f1-score	support
0	0.99	0.99	0.99	172
1	0.99	0.99	0.99	136
accuracy			0.99	308
macro avg	0.99	0.99	0.99	308
weighted avg	0.99	0.99	0.99	308

Figure 4: Classification report of the proposed CNN model

The implementation of the developed MTCNN model using different assessment parameters in terms of accuracy, recall, f1-score, support, macro avg, and weighted avg is shown in the below categorization reports. This report gives the results of the face mask dataset that is divided between 0 and 1, which means with and without mask data. All the parameters give us 99% results, while support is different, which is 172 and 136, respectively.

Table 1: Models Performance of Testing and Training Accuracy

Model	**Training Accuracy**	**Testing Accuracy**
Proposed MTCNN	99.76	99.35
Base CNN	97.87	96.75

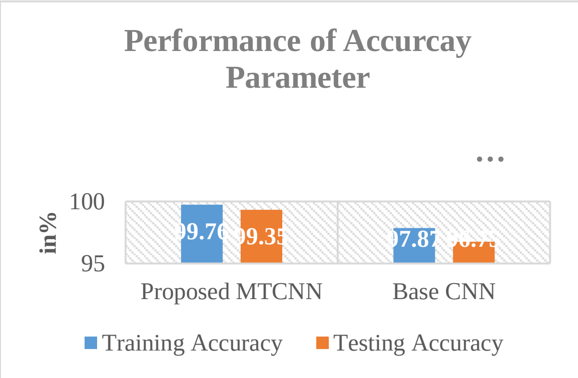

Figure 5: Comparison graph of testing and training accuracy of base and proposed models

The above figure 5 and table 1 show the testing and training accuracy of the proposed MTCNN and base CNN model. The MTCNN model achieved higher training accuracy of 99.76%, whereas the CNN model achieved a training accuracy is 97.87%, respectively. Similarly, the MTCNN mode gives a testing accuracy is 99.35% which is a minor difference compared to training accuracy, while the base testing accuracy is 96.75, which is very lower than the proposed model. So, my proposed model has achieved higher accuracy. MTCNN is a very accurate and robust model.

Table 2: Models Performance of Testing and Training Loss

Model	**Training Loss**	**Testing Loss**
Proposed MTCNN	0.0081	0.0505
Base CNN	0.0676	0.0680

VII. RESULT AND DISCUSSION

A model's errors are determined by the connection between accuracy and loss during training. The suggested confusion matrix classifies 681 samples as with a mask when they should be without a mask and 858 samples as without a mask when they should be with a mask. Training loss, validation loss, training correctness, and testing set are determined in Figures 1–5. The train and test accuracy curves were exhibited for 20 iterations. As shown in 1, the train and test performances were nearly identical. The model appears to be able to generalize unsupervised learning while detecting training samples. Nonetheless, its train and test batch loss curves tend to meet at epoch 19. The training error diminishes with more epochs. The validation error is lower than the classification technique for about 1 epoch, but then it starts to rise, suggesting that its predictions may lose confidence. Validation loss rises around the 19th epoch and stays within a reasonable range. This system's major purpose appears to be distinguishing samples with and without masks, proving its reliability.

Table 3: Mask Category with the count of classes

	classes	Count_of_Classes
0	with_mask	858
1	without_mask	681

Table 3 shows the testing accuracy/loss of the proposed MTCNN and base CNN model. The MTCNN models had a greater testing accuracy of 99.35 percent, whereas the MTCNN model had a testing loss of 0.0505 percent, the base testing accuracy was 96.75 percent, as well as the CNN testing loss, was 0.068 percent, which is much less than the proposed model,

Table 4: Testing performance

Model	**Testing Accuracy**	**Testing Loss**
Proposed MTCNN	99.35	0.0505
Base CNN	96.75	0.0680

Table 4 displays the proposed and base model's training accuracy/loss. The proposed model achieved a training loss of 0.0081%, and a training accuracy was 99.76%, whereas the base model training loss was 0.0676%, and base training accuracy was only 97.87%, respectively. Similarly, the MTCNN model gives a testing loss of 0.0505%, while the base testing loss is 0.068, which is very lower than the proposed model

Table 5: Training performance

Model	**Training Accuracy**	**Training Loss**
Proposed MTCNN	99.76	0.0081
Base CNN	97.87	0.0676

This research was entirely focused on difficult face detection, which recognizes whether or not a lady was wearing a face mask and then produces the correct result, as well as a monitoring system that employs a deep convolutional neural network and machine learning approaches by the use of MTCNN. The MTCNN-trained approach achieves 99.76 percent performance and accuracy, allowing to retain the maximum levels of accuracy, throughput, and efficiency feasible. The categorization network's findings were passed on to the proper authorities. The strategy suggested in this paper might be a helpful tool for ensuring that everyone in public settings wears a face mask.

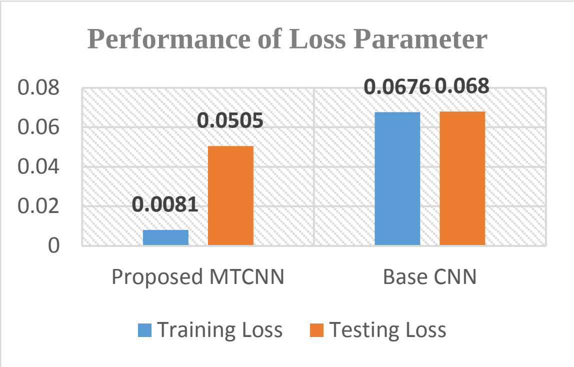

Figure 6: Comparison graph of testing and training Loss of base and proposed models

The above figure 6 and table 2 show the testing and training loss of the proposed and base model. The proposed model achieved a training loss of 0.0081%, whereas the base model training loss was 0.0676%, respectively. Similarly, the MTCC model gives a testing loss is 0.0505%, while the base testing loss is 0.068, which is very lower than the proposed model.

It seems that the first model outperforms all the others in this comparison. The best model we came up with is displayed in the graph below. In this graph, the number of epochs is plotted against training or testing/validation loss or accuracy, as well as training and testing/validation accuracy. The figure shows that as the number of epochs grows, the training & testing accuracy improves, and the testing and validation accuracy declines. In addition, the model's testing/validation accuracy is greater than its training accuracy, indicating that the model is not suffering from overfitting. The proposed model had a greater accuracy of 99.76 percent as well as a lower loss of 0.0081 percent, correspondingly.

VIII.CONCLUSION

We implemented a model that uses a real-time camera to monitor the region without the use of some other gadgets. A basic real-time picture analyzer seems to be the proposed system. It would have the capability of detecting whether people are wearing masks. That aids in the fight against the COVID-19 virus's spreading. While wearing a mask slows the transmission of the COVID-19 virus within communities. My goal aims to create a Face Mask Detection algorithm utilizing a very well Deep Learning technique to aid in pandemic preparedness. That method can be used to determine who has not been wearing the facial mask or use the classification classifier. This study presents a smart city technique for reducing total coronavirus transmissions by notifying authorities when something isn't wearing a COVID-19[16]required facial mask. Inside this study, we created the MTCNN approach. MTCNN refers to Multi-task Cascaded Convolutional Networks, and it has been created to handle problems like face comparisons or expressions of photo IDs. The method employs 3 main kinds of CNN models to memorize elements like the eye, nose, or mouth. The suggested MTCNN system detects a face mask with an experimental result indicating that now the proposed algorithm does have a detection accuracy of 99.66 percent or a loss of 0.0081 correspondingly, indicating that it would have good robustness to eye image identification of various grades. The recommended method's usefulness has been demonstrated by the experiment results. The method suggested in this work could be a valuable tool for requiring everyone here to wear a face mask during appropriate situations. Finally, we get the python output then we deployed this project in AWS platform. AWS delivers a wide variety of computing to speed deep learning training as well as inference.

Future Work

In the future, to optimize the result of face mask detection models new techniques, such as YOLOV5could be implemented which further could be applied to several applications, likethe Syed Umaid model to inspect mega solar plants. [17]and to increase the potential of wind energy[18].

REFERENCES

[1] V. Vinitha and V. Velantina, ‘Covid-19 Facemask Detection With Deep Learning and Computer Vision’, *International Research Journal of Engineering and Technology (IRJET)*, vol. 07, no. 08, pp. 3127–3132, 2020.

[2] P. F. Mulhaq and S. Suyanto, ‘Face Mask Detection on Facial Images Using Convolutional Neural Network’, 2021. doi: 10.1109/icoiact53268.2021.9564012.

[3] M. M. Rahman, M. M. H. Manik, M. M. Islam, S. Mahmud, and J. H. Kim, ‘An automated system to limit COVID-19 using facial mask detection in smart city network’, in *IEMTRONICS 2020 - International IOT, Electronics and Mechatronics Conference, Proceedings*, 2020. doi: 10.1109/IEMTRONICS51293.2020.9216386.

[4] T. Meenpal, A. Balakrishnan, and A. Verma, ‘Facial Mask Detection using Semantic Segmentation’, in *2019 4th International Conference on Computing, Communications and Security, ICCCS 2019*, 2019. doi: 10.1109/CCCS.2019.8888092.

[5] P. F. Mulhaq and S. Suyanto, 'Face Mask Detection on Facial Images Using Convolutional Neural Network', 2021. doi: 10.1109/icoiact53268.2021.9564012.
[6] H. Wang and C. Lursinsap, 'Detecting Facial Images in Public with and without Masks Using VGG and FR-TSVM Models', in *JCSSE 2021 - 18th International Joint Conference on Computer Science and Software Engineering: Cybernetics for Human Beings*, 2021. doi: 10.1109/JCSSE53117.2021.9493848.
[7] B. Wang, J. Zheng, and C. L. P. Chen, 'A Survey on Masked Facial Detection Methods and Datasets for Fighting Against COVID-19', *IEEE Transactions on Artificial Intelligence*, p. 1, 2021, doi: 10.1109/TAI.2021.3139058.
[8] Z. Song, K. Nguyen, T. Nguyen, C. Cho, and J. Gao, 'Camera-Based Security Check for Face Mask Detection Using Deep Learning', 2021. doi: 10.1109/bigdataservice52369.2021.00017.
[9] J. Vadlapati, S. Senthil Velan, and E. Varghese, 'Facial Recognition using the OpenCV Libraries of Python for the Pictures of Human Faces Wearing Face Masks during the COVID-19 Pandemic', 2021. doi: 10.1109/icccnt51525.2021.9579712.
[10] A. S. Joshi, S. S. Joshi, G. Kanahasabai, R. Kapil, and S. Gupta, 'Deep Learning Framework to Detect Face Masks from Video Footage', in *Proceedings - 2020 12th International Conference on Computational Intelligence and Communication Networks, CICN 2020*, 2020. doi: 10.1109/CICN49253.2020.9242625.
[11] M. M. Rahman, M. M. H. Manik, M. M. Islam, S. Mahmud, and J. H. Kim, 'An automated system to limit COVID-19 using facial mask detection in smart city network', in *IEMTRONICS 2020 - International IOT, Electronics and Mechatronics Conference, Proceedings*, 2020. doi: 10.1109/IEMTRONICS51293.2020.9216386.
[12] Kaggle, 'Face Mask Detection'.
[13] Github, 'Face Mask Detection'.
[14] C. Shorten and T. M. Khoshgoftaar, 'A survey on Image Data Augmentation for Deep Learning', *J Big Data*, 2019, doi: 10.1186/s40537-019-0197-0.
[15] Y. Ho and S. Wookey, 'The Real-World-Weight Cross-Entropy Loss Function: Modeling the Costs of Mislabeling', *IEEE Access*, 2020, doi: 10.1109/ACCESS.2019.2962617.
[16] M. A. Alamri*et al.*, 'Molecular and Structural Analysis of Specific Mutations from Saudi Isolates of SARS-CoV-2 RNA-Dependent RNA Polymerase and their Implications on Protein Structure and Drug–Protein Binding', *Molecules*, vol. 27, no. 19, Oct. 2022, doi: 10.3390/molecules27196475.
[17] S. U. Ahmed, M. Affan, M. I. Raza, and M. Harris Hashmi, 'Inspecting Mega Solar Plants through Computer Vision and Drone Technologies', in *Proceedings - 2022 International Conference on Frontiers of Information Technology, FIT 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 18–23. doi: 10.1109/FIT57066.2022.00014.
[18] R. Asghar *et al.*, 'Wind Energy Potential in Pakistan: A Feasibility Study in Sindh Province', *Energies (Basel)*, vol. 15, no. 22, Nov. 2022, doi: 10.3390/en15228333.