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Efficient Face Mask Detection Using Hybrid Deep Learning Algorithms

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ABSTRACT

The coronavirus COVID-19 pandemic has caused a global health crisis. According to According to the World Health Assembly, one of the best preventative measures is to wear a face mask while out outdoors (WHO). This work presents a hybrid model for face mask identification that combines deep and traditional machine learning. I have trained the proposed system, which consists of convolutional neural networks (ConNN), support vector machines (SVM), and random forests (RF), in three stages, the first stage, used ConNN, the second stage, used the same ConNN with the SVM method, and in the third stage, used ConNN and RF. This paper suggests three different kinds of masked face recognition datasets: the Incorrectly Masked Face Dataset (IMFD), the Correctly Masked Face Dataset (CMFD), and the combination for MaskedFace-Net, a worldwide masked face detection system. Two objectives are presented for the realistic masked face datasets: i) to identify individuals whose faces are covered or not covered, ii) to identify faces whose masks are put on properly or improperly (for example, at airport entrances or among crowds). The suggested model is made up of two parts. The first part is designed for feature extraction using a convolutional neural networks. In contrast, the second section is made to classify face masks using SVM and RF methods. The ConNN achieved 99.92%. and achieved for ConNN and SVM 99.94%. ConNN and RF 98.79%. Moreover,The system has been tested in real world scenarios and can recognize and classify any image selected by Google with high accuracy. we a comparison and the results aim to evaluate the proposed model.

* While CNN is an acronym for Cellular Neural Network and CoNN has long been used in the literature as an acronym for Cooperative neural networks, Convolutional Neural Network is shortened as ConNN, not CNN or CoNN.

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1. Introduction

Beginning in early 2020, The epidemic of COVID-19 impacted every country around the globe. Considering then, numerous healthcare facilities and the World Health Organization (WHO) have worked to stop the disease's spread [1]. Researchers have demonstrated that using face masks can prevent the spread of COVID-19 [39]. The

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recommended adherence to basic precautions of (WHO) by staying away from others by keeping social distance [2]. The coronavirus, the most recent pandemic virus to impact humanity was in the previous century, referred to as COVID-19 [40]. Because to COVID-19's rapid expansion, the World Health Organization was forced to declare the virus a global pandemic in 2020. According to [41]. and wearing a face mask correctly to cover the face and nose. Because of the epidemic conditions we are going through, the field of research in reducing the spread of the epidemic by using modern technology has become a very active source among researchers and scientists, and here comes the role of the artificial field and machine learning to work in limiting this spread.

Convolutional Neural Networks [3] , [4] have gained great popularity during the recent period, due to the success of deep learning in computer vision, especially considering Convid-19 pandemic, where many new recent studies of the Convid-19 pandemic have appeared, In this regard, the literature contains a few sizable datasets of face photos with protective masks associated to viruses, these investigations [5 , 6 , 7]. In several nations, people are required by law to wear face masks when they are in public. These laws and restrictions were developed in reaction to the sharp increase in incidents and fatalities that was occurring in various areas. On the other hand, keeping an eye on big crowds of people is getting harder. Finding anyone not using a face mask is part of the surveillance procedure. In France, new AI software tools are incorporated into the security cameras of the Paris Metro system to ensure that riders wear face masks [42]. focus on diagnosing the emerging corona disease, modifying the existing surveillance systems for the conditions of Covid-19 [8], [9], and building new control systems to prevent the disease [11], [12], Some studies focused on CT scans [13], [14] to diagnose the disease, the others focused on chest X-ray images [15], [16]. On the other hand, [17]. for instance, COVID-19 was found in medical chest X-rays [43]. provides age prediction. beside the face mask detection, there is also research in order to track measures to prevent the spread of the virus, There are many studies on wearing an appropriate mask [18], [19], [20], [21] and maintaining social distance between people [19] , [22] , [23] , [25]. In [9]. A single RetinaFace-based system was suggested [14]. technology to identify faces and categorize them based on whether or not they are wearing masks In [18]. The authors recommend using MobileNetV2 in conjunction with an SSDMNV2 system as a face detector [24] as a mask classifier. For masked face recognition, there are three datasets available: Masked Face Detection Dataset (MFDD), Real-World Masked Face Recognition Dataset (RMFRD), and Simulated Masked Face Recognition Dataset (SMFRD). The Real-World Masked Face Dataset (RMFD2).

In this study, we suggested to utilize Convolution Neural Network (ConNN), a kind of Deep Neural Network (DNN), which is widely used in image recognition and classification, to create a real-time facemask detection model. The suggested model can be installed in security cameras in businesses, educational institutions, malls, multiplexes, and other locations. It helps to automatically monitor people to see if they are wearing face masks; if not, it can identify them, report them to higher authorities, and send them a text message to let them know. By reducing the number of positive cases, which are steadily rising every day, and breaking the chain of infection transmission during intimate contact, this approach helps to manage the rate at which defenseless lives are lost. This research proposes a deep learning based face mask detection method. By identifying those who choose not to wear face masks, the technique outlined here may be employed in concert with surveillance footage to stop the propagation of COVID-19.

The following summarizes the planned work's main contribution:

1. Using pictures and video streams, a three-phase facemask detector was developed to help accurately detect the presence of a mask in real-time.
2. The set of photographs, both masked and revealed, is available to the public on GitHub. This data collection may be used to construct novel facial mask detection that can be used in many applications.
3. Gather photos of individuals donning masks in order to build the classifier and distinguish across classes. for those wearing faces masks and those who don't, the suggested model made use of a few well-liked deep learning techniques. This work is implemented using Keras and Open-CV in Python. Compared to other models covered, it uses less memory and processing power, making it simpler to implement for surveillance.
4. Based on the findings, the paper makes recommendations for future research aimed at creating dependable and efficient AI models that are capable of identifying faces in everyday scenarios.
5. The system has been tested in real world scenarios and can recognize and classify any image selected by Google with high accuracy.

2. DATASET

In order to make an integrated system in detecting masked faces from the faces that are not wearing them correctly or partially, we trained our system on several images, so the dataset for the images that we used is

MaskedFace-Net [38]. was published in Augest 2020, The dataset consists of many images, amounting to more than 130,000 images with a 1024x1024 size, classified into two main sections, according to Figure 1. The first one includes masked faces correctly images, and the other section includes faces that wear mask partially, which uncover the mouth, nose, or chin. Accordingly, three different kinds of masked face recognition datasets are suggested by this work: the Correctly Masked Face Dataset (CMFD), the Incorrectly Masked Face Dataset (IMFD), and Both of them (MaskedFace-Net) for the global masked recognition of faces. Two goals are given for real masked face data sets: (i) identifying individuals whose faces are masked or not, and (ii) identifying faces whose masks are worn properly or wrongly (e.g., at airport entrances or in crowds). To the best of our knowledge, no sizable face mask dataset has a classifier granularity that allows for the investigation of mask wearing. Additionally, this study introduces the applied mask-to-face deformable model worldwide, enabling the creation of additional masked face pictures, particularly with particular masks. The 133.783 photos in our masked face datasets are accessible at https://github.com/MohammedSafaa/-MaskedFace-Net-dataset. MaskedFace-Net was created using the Flickr-Faces-HQ3 (FFHQ) face image collection, which NVIDIA Corporation made openly available online [38].

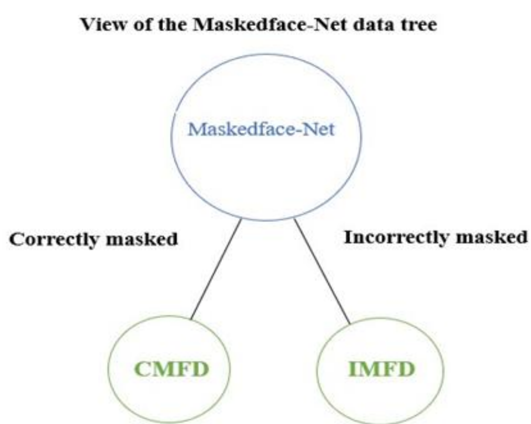

Fig. 1 - Shows the dataset tree classified into two main categories.

In figure 2, we can see some samples from the dataset, classified according to the way the mask is worn, whether it is worn correctly or partially covers the face, group (a) shows pictures of faces that wear the mask correctly, the other groups (b), (c), and (d) shows faces with partial masked.

Fig. 2 - Sample of MaskedFace-Net dataset.

2.1. Data prerocessing

In order to prepare our dataset to be ready to work on our system, with a precise accuracy, we rescaled the size of each image into 32x32 without losing the details of the masked faces to increase our system speed to train and save some hardware resources. We also train about 30000 images for both classes and keep also around 10000 images for the validation. We also merged the partial masked classes into one class, Two goals are presented for real covered face information sets: (i) identifying individuals that are masked or not, and (ii) identifying faces whose masks are worn properly or wrongly.

3. METHODOLGY

For the face detection task, we used a convolutional neural network as the base model. The model is a sequential architecture consisting of four stages of deep convolutional networks that predict facial landmarks. We trained our system, which consists of ConNN, SVM and RF, in three stages, the first stage we used ConNN, the second stage we used the same ConNN with the SVM method, and the third stage we used ConNN and RF. Our system consists of two main sections: feature extraction and faces classification.

3.1. Convloutional Neural Network (ConNN)

The convolutional neural network [3] , [4], a deep neural network involved to train on our dataset, ConNN composed of a powerful automatic feature extractor with a trainable classifier. ConNNs are used to learn complicated, high-dimensional data, and the way convolutional and sub-sampling layers are investigated differs. Their architecture is what separates them. Many ConNN designs have been proposed for various challenges, including object recognition [10]. The ConNN architecture consists of 4 repeated group of layers with different filters 32 – 64 – 64 – 128 sequentially for each group followed by pooling and fully connected layers, Figure 3. shows Proposed ConNN Architecture.

Fig. 3 - Proposed ConNN Architecture.

3.2. Proposed system

ConNNs are a deep neural network used to train on a dataset to extract features and landmarks from an image. When applied to large data, it offers protection against overflow at any level of concern. The eight layers of the proposed ConNN face mask are two-dimensional convolutional layers, with three fully connected layers and some max pooling layers in between. Training results on the tan and sigmoid revealed an improvement with the use of an unsaturated rectified linear unit (ReLU) activation function. A synopsis of the suggested architecture can be as can be shown in Table 1, which also contains details on the output forms, the values of parameter (weights) for every layer, and the total number of parameters (weights) in the suggested model.

Pre-processing completes the essential setups, while preliminary processing processes the incoming data suitable for use in the recommended classification prediction step. This phase includes actions for scaling and normalization. To enable data to be generalized and acceptable for deep learning prediction models, the most crucial step is to scale the samples' clipped picture dimensions. The total amount of pixels in sample photos must be raised or lowered in order to reconstruct an image from a one-pixel grid to another. This process is known as image scaling. To enhance the quality of the output, picture resizing utilizes an image scaling technique that estimates missing values at missing spots by interpolating known data from the surrounding pixels. When processing inputs.

Neural network models handle modest weight values. Large integer value inputs have the potential to impede or slow down the learning process. The normalization procedure modifies the input values' intensity range when seen normally, assigning a value range of 0 to 1 to every input value.

Table 1: An overview of the suggested approach.

Layer (type)	Output Shape	Parameters no.
input_1 (InputLayer)	[(None, 32, 32, 3)]	0
conv2d (Conv2D)	(None, 32, 32, 32)	896
batch_normalization (BatchNormalization)	(None, 32, 32, 32)	128
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
batch_normalization_1 (BatchNormalization)	(None, 32, 32, 32)	128
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 63)	18207
batch_normalization_2 (BatchNormalization)	(None, 16, 16, 63	252
conv2d_3 (Conv2D)	(None, 16, 16, 63)	35784
batch_normalization_3 (BatchNormalization)	(None, 16, 16, 63)	252
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 63)	0
dropout_1 (Dropout)	(None, 8, 8, 63)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	72704
batch_normalization_4 (BatchNormalization)	(None, 8, 8, 128)	512
conv2d_5 (Conv2D)	(None, 8, 8, 128)	147584
batch_normalization_5 (BatchNormalization)	(None, 8, 8, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_2 (Dropout)	(None, 4, 4, 128)	0
conv2d_6 (Conv2D)	(None, 4, 4, 256)	295168
batch_normalization_6 (BatchNormalization)	(None, 4, 4, 256)	1024
conv2d_7 (Conv2D)	(None, 4, 4, 265)	610825
batch_normalization_7 (BatchNormalization)	(None, 4, 4, 265)	1060
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 265)	0
dropout_3 (Dropout)	(None, 2, 2, 265)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 265)	0
dense1 (Dense)	(None, 256)	68096
dropout_4 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 256)	65792
dense (Dense)	(None, 2)	514
batch_normalization_5 (BatchNormalization)	Output Shape	Param
max_pooling2d_2 (MaxPooling2D)	[(None, 32, 32, 3)]	0

===

Total params: 1,328,686
Trainable params: 1,326,752
Non-trainable params: 1,934

3.3. Support Vector Machine (SVM)

Belong to ConNN we also use in our study SVM which is proposed by Vapnik [25], The goal of is to develop a separation hyperplane that maximizes the distance between the margins of two different classes of classifications. SVM is used to create a suitable separation hyper-plane (equation 1) or decision surface even in cases where the data are linearly inseparable. This is achieved by utilizing a novel technique that involves mapping the sample points into a high-dimensional feature space and classifying them through a nonlocal transformation. The optimal hyper-plane can be discovered by applying regularization parameters to solve a quadratic programming issue. Kernel functions include polynomial, sigmoid, linear, and radial basis functions. were used to do this modification [36],[37]. We applied the SVM system for classifying our data on the output of the ConNN feature extraction.

- A kernel that is linear: $K(x, y) = x \times y$ (1)
- A polynomial kernels: $K(x, y) = [(x \times y) + 1]d$ (2)
- The Sigmoid kernel: $K(x, y) = tanh\,(\beta 0\, x\, y + \beta 1)$ (3)
- RBF kernel $K(x, y) = exp(-\gamma\,||x - y||2)$ (4)

  With d, $\beta 0$, $\beta 1$, and γ are parameters that will be determinate empirically.
- $\text{f}(x) = WT\,\Phi(x) + b$ (5)

  Where $W\ \varepsilon\ Rn$, $\Phi(x)$ is a feature map.

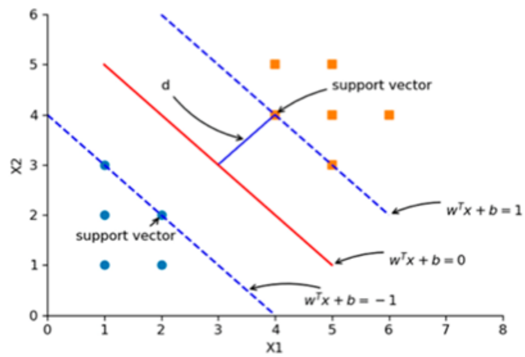

Fig. 4 - shows the binary classification of support vector machine.

3.4. RandomForest (RF)

Building an ensemble of unpruned decision trees using training data and randomized components is a supervised learning technique for classification and regression. When the majority of the trees vote for a certain class, a process called as voting, the RF prediction is made. ConNN-RF combines ConNN's superior feature extraction capabilities with the long-term robustness of RF categorization.

3.5. Suggested model methodology

Deep transfer learning is the first of the two primary components of the suggested approach using convolutional neural networks (ConNN) as a feature extractor and the second component is classical machine learning such as random forest and SVM algorithms. According to [44,45], the convolutional neural network algorithm achieved better results when used as a feature extractor. Figure 5 shows A diagram representing the system architecture. Basically, ConNN is used for the feature extraction stage, while the traditional machine learning model is used in the training, validation, and testing stages.

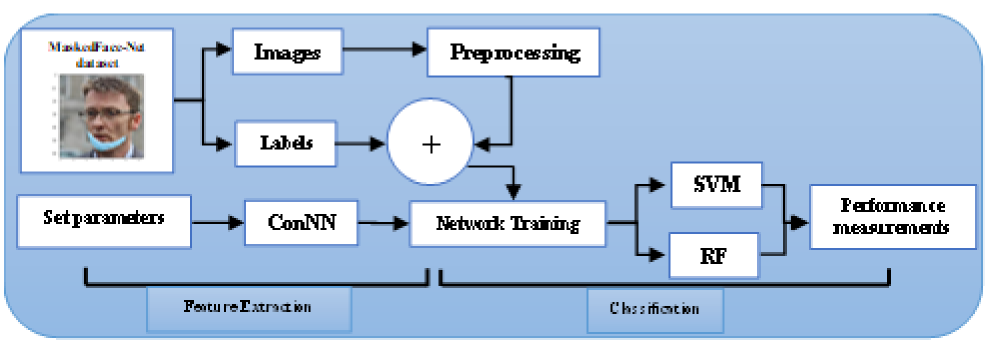

Fig. 5 - diagram representing the system architecture.

In classification, the last layer in the convolutional neural network is eliminated and conventional machine learning classifiers installed in their stead (svm and RF) to improve the performance of our model. The main contribution of this research is to create SVM and RF that do not overfit the training process.

3.6. Performance Metrics

The suggested ConNN model, which is based on deep learning, is assessed for accuracy image classification and face mask detection. Through this research, performance matrices need to be examined to evaluate the effectiveness of different classifiers. The most frequently calculated performance metrics are precision, accuracy, recall, and F1 score [46], which are listed in order of presentation in Equations (1) to (4).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

$$\text{Precision}=\frac{TP}{TP+FP} \qquad (2)$$

$$\text{Recall}=\frac{TP}{TP+FN} \qquad (3)$$

$$\text{F1 score}= 2*\frac{(Precision * Recall)}{(Precision+Recall)} \qquad (4)$$

where the counts of True Positive, True Negative, False Positive, and False Negative samples are represented by the letters TP, TN, FP, and FN in a confusion matrix.

Table 2- ConNN Simulation parameters.

Parameters	Value
Input size	32 × 32 × 3
Optimizer	Optimizers adam
Loss	Binary cross-entropy
Learning rate	0.0001
Batch Size	32
Epochs	10
Activ function	Relu
Steps per epochs	100
Validation steps 10	100

3.7. Training and Results

After preparing the dataset, we trained it with our system which consists of ConNN, SVM and RF, on three stages, the first stage we used ConNN, the second we used same ConNN with SVM method, and the third stage was using ConNN and RF, and we achieved the results in table 3 showing the accuracy for each system.

Table 3- Shows the results for each system.

Method	Accuracy	F1-Score	Faces
ConNN	99.92%	1.00	
ConNN + SVM	99.94%	1.00	133.783
ConNN + RF	98.79%	1.00	

Table 4- A comparison between our suggested methodologies and recent works.

Reference	Proposed technique	No of classes	Result
[28]	Cascade network of two levees, (DRFL) Network and SRNet20 network.	3	90.6% on the wider face dataset and 98.5% on prepared dataset
[29]	SSD model, Hourglass network, FaceNet	3	
[30]	CNN, AlexNet, VGG16, and FaceNet	CNN of 2 classes AlexNet of 4 classes	97% accuracy
[31]	YOLOv4	3	98.3%
[32]	CNN	2	97.14%
[33]	MobileNet	2	93.14%
[34]	InceptionV3	2	100%
[35]	Resnet50, decision trees, SVM and ensemble algorithm.	2	99.64% in RMFD and 99.49% in SMFD
[36]	CNN,CNN with SVM, CNN with RF.	3	96.19% in FMLD and 96.11% 96.28% on prepared dataset
Proposed ConNN	Based on VGG16	2	99.92%
Proposed model with SVM,RF	ConNN With SVM	2	99.94%
	ConNN With RF	2	98.79%

In figure 6 below, we show the prediction for each system with 2 classes: incorrect mask face detection (IMFD) and correct mask face detection (CMFD), as well as the confusion matrix for each system.

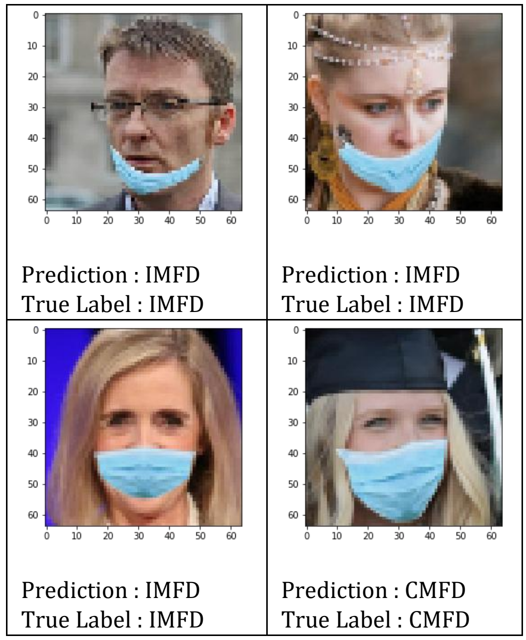

Fig. 5 - Random Results for proposed system

Using our proposed ConNN, which aims to learn each pixel value in a rectangular region containing masked and unmasked faces quickly and with high functionality and perform fast queries, the system was trained on the Google Colab environment and Python programming language, with batch size 32 and input format 64, and we achieved an accuracy of about 99.92% with a loss of 0.15 after 10 epochs. Figures 7 and 8 show the accuracy and loss metrics of our proposed ConNN.

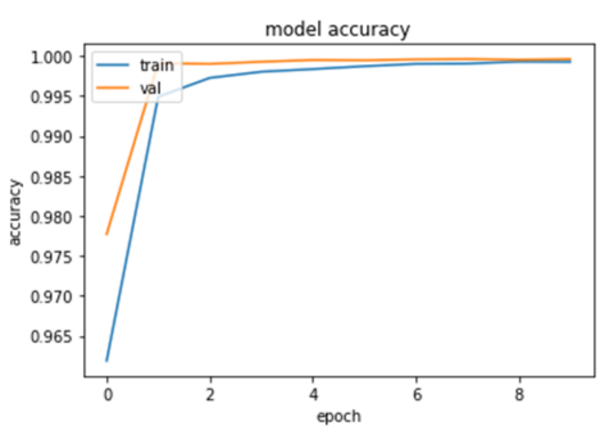

Fig. 7 - Proposed ConNN Accuracy metrics

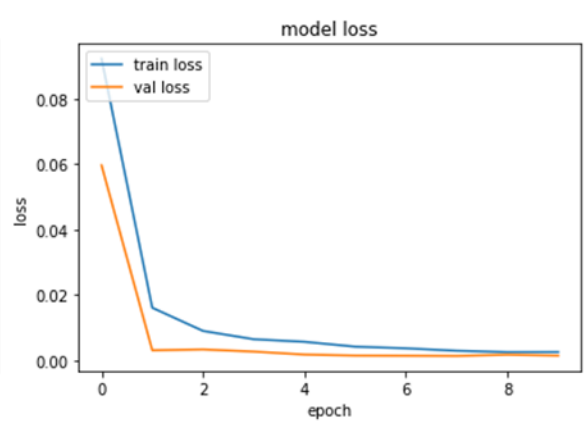

Fig. 8 - Proposed ConNN Loss metrics

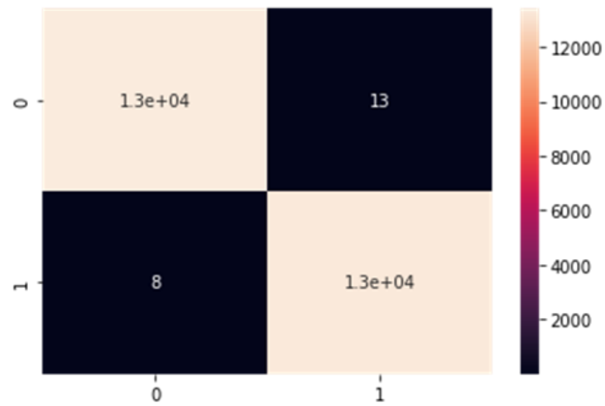

Fig. 9- Confusion Matrix ConNN

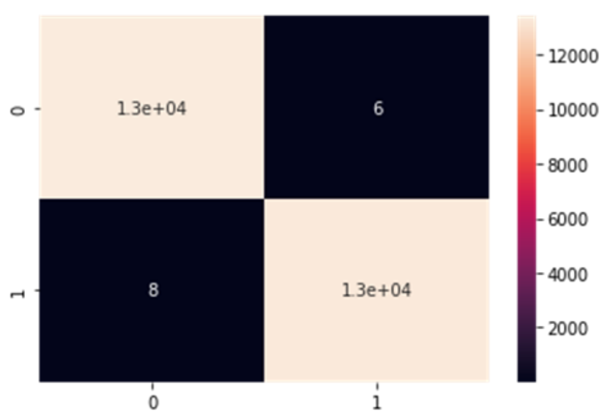

Fig. 10 - Confusion Matrix ConNN +SVM

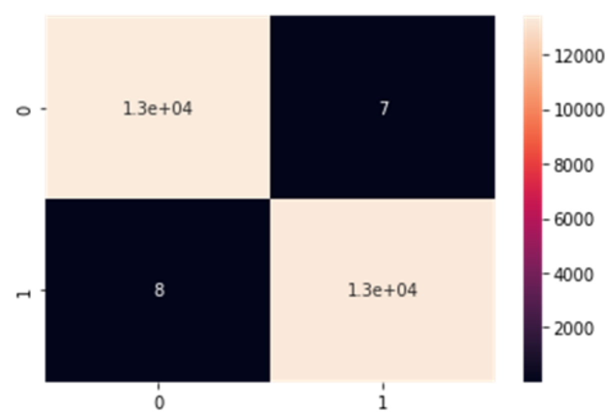

Fig. 11 - Confusion Matrix ConNN +RF

4. Results And Discussion

The work presents an integrated model of a face mask detection system. To take the necessary precautions against the Corona virus epidemic and other diseases that are spreading rapidly, it is necessary to use surveillance cameras to spy and track unmasked people in public and crowded places. In this part, we examine the model's performance using the dataset MaskedFace-Net The dataset consists of many images.

We also made a comparison between our system and the most advanced mask detection systems available today, which include a deep learning-based system, Two levees' cascading networks, the SRNet20 network and the DRFL network [28]. a real-time mask detection system based the Hourglass network, FaceNet, and SSD model [29]. an enhanced CNN, AlexNet, VGG16, and FaceNet, faces detection model [30], a deep learning CNN-based approach for mask detection [32], and a YOLOv4-based [31]. approach MobileNet [33].a real-time mask detection system based on Resnet50, decision trees, SVM and ensemble algorithm [35]. approach InceptionV3-based [34]. The systems' performance comparison on the test dataset is displayed in Table 3. The efficacy of the suggested system in identifying mask in real-world situations was demonstrated by its superior performance over the current methods in terms of precision, recall, and F1-score.

In order to prepare our dataset to be ready to run on our system, with precise resolution, we resized each image to 32 x 32 x 3 without losing details of the masked faces to increase the speed of our system for training and preservation. Some hardware resources. We also train about 30,000 images for both classes and also keep about

10,000 images for validation. We also combined the partially masked categories into a single category, so that the result of the dataset was either correctly masked or not properly masked. We found that the accuracy achieved when using ConNN was 99.92%, and only a small amount of confusion was observed between wearing the mask incorrectly and misclassifying 8 images. The performance of ConNN is also improved when using SVM as a classifier. An accuracy of 99.94% was achieved using real data, with 7 misclassified images. and to 98.79% using ConNN+RF, with 8 images being misclassified. Furthermore, we compared the results between the three systems and presented the results of each system.

5. Conclusion

To limit the spread of the new mutant Corona pandemic and other rapidly spreading diseases, we demonstrated a mask detector system consisting of a convolutional neural network for feature extraction purposes, a support vector machine, and a random forest method for classification methods. In this part, we examine the model's performance using the dataset discussed in Section II. Initially, we used the ConNN classifier described in Section II to perform face mask classification. Then, to improve the classification accuracy of ConNN, we used SVM and RF as classifiers for the features extracted by the convolutional layers.The system has been tested in real world scenarios and can recognize and classify any image selected by Google with high accuracy. and we compared the results between the three systems and presented the results of each system.

References

[1] https://www.who.int/.Accessed April 2021

[2] 2Glogowsky, E. Hansen, and S. Schächtele, "How effective are social distancing policies? Evidence on the fight against COVID-19," PLOS ONE, vol. 16, no. 9, p. e0257363, Sep. 2021, doi: 10.1371/journal.pone.0257363.I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[3] Gu et al., "Recent Advances in Convolutional Neural Networks," ArXiv151207108 Cs, Oct. 2017, Accessed: Jan. 18, 2022. [Online]. Available: http://arxiv.org/abs/1512.07108R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[4] Q. Zhang, M. Zhang, T. Chen, Z. Sun, Y. Ma, and B. Yu, "Recent Advances in Convolutional Neural Network Acceleration," Neurocomputing, 2019, doi: 10.1016/j.neucom.2018.09.038.

[5] A. J. Sathyamoorthy, U. Patel, Y. A. Savle, M. Paul, and D. Manocha, "COVID-Robot: Monitoring Social Distancing Constraints in Crowded Scenarios," ArXiv200806585 Cs, Aug. 2020, Accessed: Jan. 18, 2022. [Online]. Available: http://arxiv.org/abs/2008.06585

[6] Senqiu Chen, Wenbo Liu, and Gong Zhang. Efficient transfer learning combined skip-connected structure for masked face poses classification. IEEE Access, 12, 2021.

[7] M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, "A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic," Measurement, vol. 167, p. 108288, Jan. 2021, doi: 10.1016/j.measurement.2020.108288.

[8] Y. LeCun, F.J. Huang, L. Bottou, "Learning methods for generic object recognition with invariance to pose and lighting," Proc. Computer Vision and Pattern Recognition Conference (CVPR), IEEE Press, 2004.

[9] G Jignesh Chowdary, Narinder Singh Punn, Sanjay Kumar Sonbhadra, and Sonali Agarwal. Face mask detection using transfer learning of inceptionv3. In Intl. Conf. on Big Data Analytics, 2020.

[10] Aniruddha Srinivas Joshi, Shreyas Srinivas Joshi, Goutham Kanahasabai, Rudraksh Kapil, and Savyasachi Gupta. Deep learning framework to detect face masks from video footage. In CICN, pages 435–440. IEEE, 2020

[11] Jun Chen et al. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution com- puted tomography. Scientific reports, 2020.

[12] Lin Li et al. Using artificial intelligence to detect covid-19 and community-acquired pneumonia based on pulmonary ct: evaluation of the diagnostic accuracy. Radiology, 296(2), 2020.

[13] Muhammad Farooq and Abdul Hafeez. Covid-resnet: A deep learning framework for screening of covid19 from ra- diographs. arXiv preprint arXiv:2003.14395, 2020.

[14] Ali Narin, Ceren Kaya, and Ziynet Pamuk. Automatic de- tection of coronavirus disease (covid-19) using x-ray im- ages and deep convolutional neural networks. arXiv preprint arXiv:2003.10849, 2020.

[15] R. Golwalkar and N. Mehendale, "Age Detection with Face Mask Using Deep Learning and FaceMaskNet-9," Social Science Research Network, Rochester, NY, SSRN Scholarly Paper ID 3733784, Nov. 2020. doi: 10.2139/ssrn.3733784.

[16] Preeti Nagrath, Rachna Jain, Agam Madan, Rohan Arora, Piyush Kataria, and Jude Hemanth. Ssdmnv2: A real time dnn-based face mask detection system using single shot multibox detector and mobilenetv2. Sustainable cities and society, 2021.

[17] Nenad Petrovic ́ and Ðord ̄e Kocic ́. Iot-based system for covid-19 indoor safety monitoring. preprint), IcETRAN, 2020.

[18] Zhongyuan Wang et al. Masked face recognition dataset and application. arXiv preprint arXiv:2003.09093, 2020.

[19] ZekunWang,PengweiWang,PeterCLouis,LeeEWheless, and Yuankai Huo. Wearmask: Fast in-browser face mask detection with serverless edge computing for covid-19. arXiv preprint arXiv:2101.00784, 2021.

[20] Adarsh Jagan Sathyamoorthy, Utsav Patel, Yash Ajay Savle, Moumita Paul, and Dinesh Manocha. Covid-robot: Monitor- ing social distancing constraints in crowded scenarios. arXiv preprint arXiv:2008.06585, 2020.

[21] Mahdi Rezaei and Mohsen Azarmi. Deepsocial: Social dis- tancing monitoring and infection risk assessment in covid-19 pandemic. Applied Sciences, 10(21):7514, 2020.

[22] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zh- moginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In CVPR, pages 4510–4520, 2018.

[23] Dongfang Yang, Ekim Yurtsever, Vishnu Renganathan, Keith A Redmill, and Ümit Özgüner. A vision-based social distancing and critical density detection system for covid-19. arXiv preprint arXiv:2007.03578, pages 24–25, 2020.

[24] X. Lin, C. Zhao, and W. Pan, "Towards Accurate Binary Convolutional Neural Network," ArXiv171111294 Cs Stat, Nov. 2017, Accessed: Jan. 18, 2022. [Online]. Available: http://arxiv.org/abs/1711.11294

[25] C. Cortes and V. Vapnik, “Support vector network,” Machine Learning, vol. 20, no. 3, pp. 273-297, 1995.
[26] Cabani, Adnane, et al. "MaskedFace-Net–A dataset of correctly/incorrectly masked face images in the context of COVID-19." Smart Health 19 (2021): 100144.
[27] Savaş, Burcu Kir, and Yaşar Becerikli. "Real time driver fatigue detection system based on multi-task ConNN." Ieee Access 8 (2020): 12491-12498.
[28] Zhu, Rui, et al. "Masked face detection algorithm in the dense crowd based on federated learning." Wireless Communications and Mobile Computing 2021 (2021): 1-8.
[29] Kong, Yinghui, et al. "Recognition system for masked face based on deep learning." 2nd International Conference on Computer Vision, Image, and Deep Learning. Vol. 11911. SPIE, 2021.
[30] Song, Ziwei, et al. "Spartan face mask detection and facial recognition system." Healthcare. Vol. 10. No. 1. MDPI, 2022.
[31] J. Yu and W. Zhang, “Face mask wearing detection algorithm based on improved YOLO-v4,” Sensors, vol. 21, no. 9, May 2021, doi: 10.3390/s21093263.
[32] M. S. Mazli Shahar and L. Mazalan, “Face identity for face mask recognition system,” in 11th IEEE Symposium on Computer Applications and Industrial Electronics (ISCAIE), Apr. 2021, pp. 42–47, doi: 10.1109/ISCAIE51753.2021.9431791.
[33] M. Z. Asghar et al., “Facial mask detection using depthwise separable convolutional neural network model during COVID-19 pandemic,” Frontiers in Public Health, vol. 10, Mar. 2022, doi: 10.3389/fpubh.2022.855254.
[34] G. Jignesh Chowdary, N. S. Punn, S. K. Sonbhadra, and S. Agarwal, “Face mask detection using transfer learning of InceptionV3,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 12581, Springer, Cham, 2020, pp. 81–90.
[35] M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, “A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic,” Measurement, vol. 167, Jan. 2021, doi: 10.1016/j.measurement.2020.108288.
[36] AL-ABBASI, M. Evrişimsel Sinir Ağı, Destek Vektör Makineleri ve Rastgele Orman Kullanarak Yüz Maskesi Algılama 4. Uluslararası Mühendislik Araştırmaları Sempozyumu, Düzce, Türkiye, 04-06 Mart 2022.
[37] Wright, mohammed, et al. Face mask detection using convolutional neural networks. Computer Engineering Department, Kocaeli University, Türkiye, 2022, No:745000.
[38] Our datasets of masked faces are available at https://github.com/MohammedSafaa/-MaskedFace-Net-dataset.
[39] S. Feng, C. Shen, N. Xia, W. Song, M. Fan, B.J. Cowling, Rational use of face masks in the COVID-19 pandemic, Lancet Respirat. Med. 8 (5) (2020) 434–436, https://doi.org/10.1016/S2213-2600(20)30134-X.
[40] X. Liu, S. Zhang, COVID-19: Face masks and human-to-human transmission, Influenza Other Respirat. Viruses, vol. n/a, no. n/a, doi: 10.1111/irv.12740.
[41] “WHO Coronavirus Disease (COVID-19) Dashboard.” https://covid19.who.int/(accessed May 21, 2020).
[42] Fouquet, H. "Paris tests face-mask recognition software on metro riders." Bloomberg. https://www. bloomberg. com/news/articles/2020-05-07/paris-tests-face-mask-recognition-software-on-metro-riders. Accessed 31 (2021).
[43] Loey, Mohamed, Florentin Smarandache, and Nour Eldeen M. Khalifa. "Within the lack of chest COVID-19 X-ray dataset: a novel detection model based on GAN and deep transfer learning." Symmetry 12.4 (2020): 651.
[44] P. Khojasteh, et al., Exudate detection in fundus images using deeply-learnable features, Comput. Biol. Med. 104 (Jan. 2019) 62–69, https://doi.org/10.1016/j.compbiomed.2018.10.031.
[45] L. Wen, X. Li, L. Gao, A transfer convolutional neural network for fault diagnosis based on ResNet-50, Neural Comput. Appl. 32 (10) (2020) 6111–6124, https://doi.org/10.1007/s00521-019-04097-w.
[46] Goutte, Cyril, and Eric Gaussier. "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation." European conference on information retrieval. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005.