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Improving The Accuarcy of Face Mask Detector System Using Machine Learning Algorithms

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Abstract:

The COVID-19 continues to have a world-wide impact on us since its inception until late in the year 2019. Easy to see with the naked eye the way coronavirus has affected human celebration and function in the past the use of multiple face masks, in many cases of government or business licensing designed to slow the spread of the disease by preventing the spread of the respiratory virus nose and mouth. Wearing a mask is considered an effective means of preventing the spread of the coronavirus during the COVID-19 pandemic. Tools of Machine Learning such as TensorFlow, Keras, OpenCV, and Scikit-Learn are used to develop a face mask detector system. The preparation process was completed to identify the human face in the picture or photo and then to determine if it had a face mask on it. As the observation works, it can also identify faces and faces in motion and in video. These procedures are very accurate. This mask can be used at school / college to supervise students in the classroom who are not wearing masks.

Keywords —**Occlusion, face mask, machine learning, COVID-19, deep learning.**

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I. INTRODUCTION

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In recent decades, facial recognition has become an international study [1]. In addition, with the advancement of technology and the rapid development of intelligence, significant achievements have been made [2]. For this reason, public and private companies use face recognition to identify and control human access to airports, schools, offices, and other places [3]. On the other hand, with the widespread spread of COVID-19, government agencies have adopted a number of safety policies to limit the spread of the disease [4]. One of them is the need to use masks in public places, because they have been found to be effective in protecting users and those around them [5] .

The efficiency of the measurement is an examination of each fine-grained image and depth separate chart to identify attack masks. Now research to measure the effectiveness of prevention by connections by all both texture and depth images in the mask database are included scores and level feature for better performance [6].

This clarifies the need to develop procedures to identify wearers [7]. This makes it necessary to apply new technologies to achieve the strengths of current systems [8].

The author proposed LeNet-5 network architecture, which is classic the operation of convolutional neural networks has provided effective support for the development of convolutional neural networks computer vision. However, due to the impact of energy counts and lack of data set the time, the neural network model is surpassed by the effect of SVM in certain power applications [9].

Therefore, in recent years, equipment has been adapted to meet human needs, as developed in [10], in agriculture [11], military [12], and medicine [13], etc. Involvement of this type of neural network has also been used to identify dental imaging, which is described in the review of [14]. In [15], an imaging examination was requested to examine the blood in the color image by selecting sampling data. On the other hand, in [16], an analysis of the involvement of CNNs in mammographic mammography (MBCD) was presented. Although there is some research, they are still in their infancy, with the clear goal of providing a powerful tool for the future. In [17], the study described which aims to determine the progression of CNNs in magnetic resonance imaging (MRI). Although it is used in non-novel drugs, it has now been specifically targeted to applications related to COVID-19 [18]. Several methods and procedures are used to diagnose the disease, one of which is the evaluation of computed tomography. For this reason, [19] designed a rapid and effective lung cancer-based AI (10 CNN). The results showed a very sensitive, unique and accuracy of more than 99%. Similarly, in [20], an automatic virus test using the EfficientNet architecture is described. The results showed a true average of more than 96%, confirming the involvement in the content of health. Radiography is another way to identify the impact of the disease on the patient's chest [21]. Based on this, an in-depth study based on nCOVnet network was planned in [22] for diagnostics, and the results showed that the accuracy was between 98% and 99%. A similar process was achieved in [23], which examined chest X-ray images and compared them to a variety of network configurations, achieving 98.33% accuracy when using ResNet-34. Although most CNNs are used for the diagnosis of COVID-19, they can also be used in other applications as part of the prevention of infectious diseases [24].

On the other hand, [25] describes a system for face-to-face detection using a vector vector (SVM) algorithm. These files include the Real World Masked Faces Dataset (RMFD), the Simulated Masked Faces Dataset (SMFD), and the Wildlife Registration List (LFW). The results showed that the accuracy of SVM was 99.64% in RMFD, 99.49% in SMFD and 100% in LFW. In [26], InceptionV3 conversion training was used, which achieved 99.92% accuracy during training and 100% accuracy when tested with SMFD data. In [27], one way to verify the accuracy of the mask application was defined by combining the distribution and super-resolution images (SRCNet). It achieves an accuracy of 98.70%, exceeding the image distribution of this type. Face problems due to the use of face masks during the COVID-19 epidemic have brought expertise to explore new horizons, a challenge for scientists, which has led to an improvement of the visual field as a result of the equivalence.

In [28], face recognition was learned using visual data requested by ImageNet and CNN. The results showed a accuracy of 90-95%. Similarly, [29] applied for face recognition using SVM and our data (UBIPr, Color FERET and Ethnic Ocular). Performance measurements showed 92% yield. In addition to the tasks described in the journal, the records provided people with facial expressions, whether or not they wore a face mask. Finally, this paper divides the work into four sections, section 2 contains information and procedures, section 3 presents the results, and section 4 presents the discussion.

II. DATASET ANALYSIS

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This dataset was taken from the class students and teachers. The images used in the data sets are

Categorized in two classes:

• With Mask

: 190

• Without Mask

: 186

Few sample images from the dataset are shown in Figure. 1.

Figure1: Sample images from the dataset.

III. PROPOSED METHODOLOGY

Thick face training is essential to get a beautiful face. In order to provide sufficient training materials, the only solution is to draw a human face. However, today the most popular websites do not provide accurate and easy to change confidential information. Inspired by face mask detection system, we got the mask together to get more face. Specifically, we apply the texture of the mask to the face, and then work through it to create the mask. The principle of the process is to create a map of the texture of the face and use 3D methods to create the image of the face. The masks are then blended according to texture. Using the mask-to-face combination we use, the mask can be adjusted to suit different areas of the face.

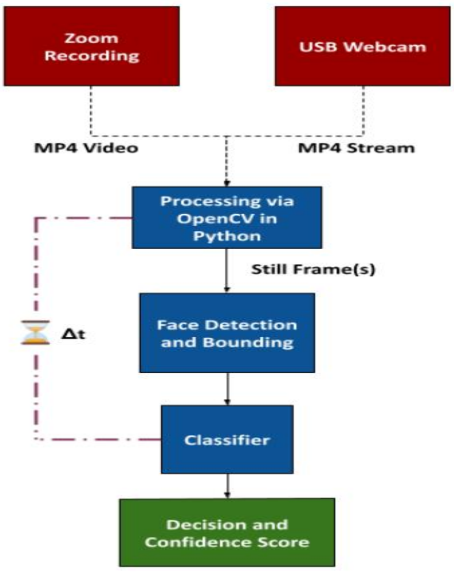

Figure2: Preliminary Architecture.

IV. RESULTS AND DISCUSSION

Using the results obtained during the training, the accuracy, sensitivity and uniqueness were calculated - the results are shown in Table 1. The results confirm the performance of products in the test of whether there is a face mask. It can be seen that the value of F1-score for both classes (masked and unmasked) is close to 1, indicating the performance of the model. In addition, when looking at avg weight, it can be determined that for two classes, the model works correctly regardless of the amount of data in each class.

TABLE I
METRICS FOR EACH CLASS (WITH FACE MASK)

	Precision	Recall	F1-Score
Face mask	0.99	1.00	0.99
No face mask	1.00	1.00	1.00
Accuracy			1.00
Macro avg	0.99	1.00	1.00
Weighted avg	1.00	1.00	1.00

For face recognition models, 20% of the data were used for training and 80% for attempts to avoid pattern overtraining. Figure 3 shows a parallel diagram for facial recognition using facial expressions.

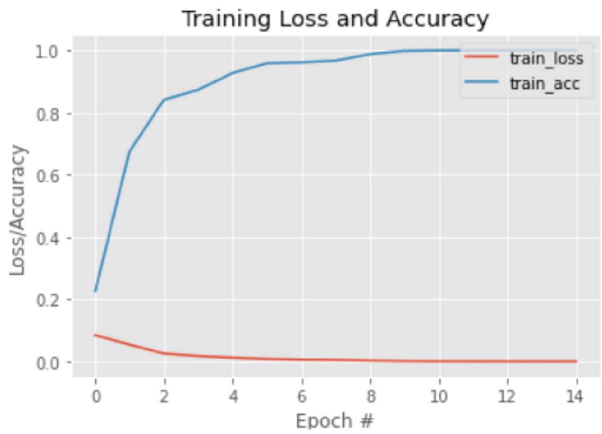

Figure3: Training loss vs. accuracy in a Face Mask Recognition (FMR) Model.

In this model, convergence is reached in about 10 times with 98% accuracy. When the model was analyzed from the test data, the accuracy was 99.52%, which resulted in the deformation matrix seen in Figure 4.

```
[[352   1   1   0   0   0   1   0   6   0]
 [  0 896   1   0   0   0   0   0   0   0]
 [  0   0 386   0   0   0   0   0   0   0]
 [  2   1   1 818   0   0   4   2   0   0]
 [  0   0   0   0 416   0   0   0   0   0]
 [  0   0   1   0   0 283   0   0   0   0]
 [  0   0   0   0   0   0 982   0   0   0]
 [  0   0   0   0   3   0   0 915   0   0]
 [  3   0   0   0   0   0   0   0 208   0]
 [  0   0   0   0   0   0   0   0   0 437]]
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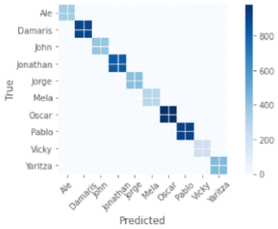

Figure4: Confusion matrix in FMR model.

Looking at the F1-scores, we can see that almost all scores are closer to 1. When comparing these results with the weighted avg, it can be seen that each class performs well even though what the situation is? The cost of materials is available in each class.

Figure5: Testing for finding the without mask persons.

V. CONCLUSION

The design model allows for face-to-face recognition of people with and without masks, and can be used as a low-cost, multi-use procedure for control personnel. Both models of the system have been graphically tested, resulting in better accuracy and refinement for each model. A person's face found in the case file is successfully subdivided into complete names and may be effective. The three levels of the system allow the isolation of facial features to perform the division of tasks using a simple neural network. In this sense, using "face embedding" as an input to the neural network yields interest in the experiment.

The system shows potential for different facial recognition applications. It is important to note that if no face is visible in the data, it will be detected, but "mask" or "no mask" will be added, refers to what the person is wearing. It is 99.65% accurate in meaning that people wear masks. The face recognition model was evaluated with the measurement data of people who do not wear face mask, and the accuracy rate is up to 99.96%, while for those who wear masks, the value is up to 99.52%. In this way, a foundation for future research that can expand research in this field.

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