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Machine Learning and Deep Transfer Learning approaches were used to create a Face Mask Identification model for COVID-19

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Abstract- COVID-19 pandemic has led to an international health emergency the WHO considers wearing a face mask an appropriate form of public health protection. This work will describe a face mask identification model that incorporates both deep and traditional machine learning techniques. Parts of the suggested model can be divided into two. Using Resnet50, the initial part of the system is set up for feature extraction. The second component classifies face masks using decision trees, support vector machines (SVMs), and the ensemble approach. The research will focus on three face-masked datasets.The Real-World Masked Face Dataset Includes three datasets: real-world masked faces, simulated faces, and wild faces (LFW). 99.64% of RMFD's SVM classifier is accurate throughout testing.. It achieved a 99.49% accuracy rate in SMFD and a 100% accuracy rate in LFW.

I.INTRODUCTION

There has been an upsurge in the use of face masks in public since the COVID-19 coronavirus epidemic broke out. Prior to the development of Covid-19, people used masks to protect their health from the harmful effects of pollution. Others prefer to keep their emotions hidden from others by concealing their faces rather than being self-conscious about their appearance.Scientists have shown that COVID-19 transmission is reduced when people use face masks. It is believed that COVID-19, also known as coronavirus, is the most recent human-pathogen encounter of the preceding century.COVID-19 has been declared a global pandemic by the World Health Organization (WHO) because of its rapid spread. In less than six months, approximately five million people in 188 countries have been exposed to COVID-19. An infectious disease can spread through intimate contact and densely populated areas[1].

Because of the coronavirus outbreak, scientists from all around the world have come together in unprecedented numbers.AI that uses deep learning and machine learning can be used to tackle Covid-19 in a variety of ways. Scientists and medics may use machine learning to predict the spread of COVID-19, serve as an early warning system for future pandemics, and classify vulnerable people[2]. Investing in cutting-edge healthcare technology like IoT and machine learning is essential to keep up with and prevent the emergence of new diseases. The CDC has implemented a tracking system to have a better sense of infection rates and swiftly identify diseases.

Artificial Intelligence (AI) is being used to fight cancer by detecting Covid-19 in chest X-rays[3].

The spread and transmission of COVID-19 pose several concerns and hazards for policymakers. There are regulations in several nations that require people to cover their faces while in public. As a response to the rapid rise in cases and deaths across several fields, these regulations and legislation were established. Monitoring big crowds, on the other hand, is getting increasingly challenging.

Surveillance personnel are looking for anyone who isn't wearing a face mask at all times. Delhi Metro security cameras are now equipped with sophisticated AI technologies to check that all passengers wear face masks. For DatakaLab, the purpose was not to identify or apprehend persons without masks; instead, it was to provide anonymous statistical data that may assist authorities in anticipating COVID-19 breakouts [4].

Deep transfer learning and standard machine learning classifiers were utilised for the mask face detection model. To prevent the spread of COVID-19, it is advised that this model be used in combination with security cameras to identify those who are not wearing face masks [5]. The model combines machine learning with deep transfer learning. The classic machine learning methods have been combined with deep transfer learning to extract characteristics from data.Training and detection algorithm comparisons yielded superior results, with the least amount of time invested and maximum accuracy.

II.LITERATURE STUDY

When it comes to face masks, the majority of the articles discuss how to construct a person's face and how to tell if they're wearing one. People who aren't using face masks might spread COVID-19; therefore, we need to find them out.According to researchers and experts, the distance of COVID-19 can be reduced by using face masks. Researchers came up with a novel approach for determining if a person has a face mask on. They could classify facemask-wearing situations into three distinct categories [6].When it comes to donning a facemask, there are three options: do it right, do it wrong, or don't wear one at all. During the phase of detecting faces, it is 98.70 % successful. Because of the mask, the PCA's ability to detect face resonation was significantly impaired because of the show. When the recognised face is hidden, recognition accuracy drops below 70%. In addition, PCA was used. On the frontal face of an individual, they devised a method to remove their spectacles. It was necessary to use recursive error compensation with PCA reconstruction to recreate the section that had been excised [7].

For face detection, the researchers turned to the YOLOv3 algorithm. The backbone of YOLOv3 is the Darknet-53. We were able to obtain a precision rate of 93.9 per cent using our new approach. More than 20,000 photos from the CelebA and WIDER FACE datasets were used to train this model. The FDDB data was put to the test.Automated removal of masks covering the face may be accomplished using a novel GAN-based network proposed by Nizam et al. As a result, the model's output depicts the full face naturally and realistically.

The authors showed an operating room mask need determination method.False-positive detections of faces are a significant concern, although surgical masks are also kept in mind. 95 % of the time, the recommended system works [8].

MRGAN, a technique that incorporates user input, was introduced by Muhammad et al. The approach relies on obtaining the user's microphone area and then rebuilding it using the Generative Adversarial Network. Shaik and colleagues employed deep learning real-time facial emotion categorization and identification. Seven face expressions were classified using VGG-16. Based on the KDEF dataset, the suggested model was shown to be 88% accurate [9].

III.METHODOLOGY

Deep transferring learning (ResNet50) is a feature extractor in this model, while classic machine learning methods including decision trees, SVM, and ensembles are essential components. ResNet-50 is an excellent feature extractor when used this way. An example of a conventional transfer learning paradigm is shown in Figure 1.However, the ResNet50 feature extraction model is mainly utilised in training and validation stages of machine learning models.

A neural network called ResNet performs deep transfer learning using residual learning as a foundation.One of the main goals of ResNet is to eliminate the vanishing gradient problem produced by a specific residual block in the model. ResNet-50's 50-layer structure features 16 remaining bottleneck blocks with three convolution layers each,First putting in a convolution layer, then a fully linked layer, and finally putting everything together.

As a result, three traditional machine learning classifiers were substituted with the final layer of

ResNet-50 (SVM). This work's most important finding is using SVMs, decision trees, and costumes that aren't overfitting in training.

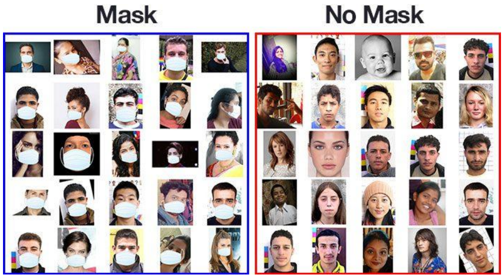


Fig. 1. Dataset images samples on RFMD

Fig. 2. Image Samples from datasets.

SVM is one of the most widely used and unique methods for pattern classification and regression.There are three parts to SVM's classification machine learning algorithm: an input vector I, a set of linear classifier coefficients (x) and (c) as given in Eq. (1). This hinge function-based classifier uses SVM to classify data

$$hj = MAX(1{,}0 - yj(x.Ji - a)) \qquad (1)$$

$$left = \frac{1}{m}\sum_{j=1}^{m} MAX(1, Jh) \qquad (2)$$

The decision tree is a categorization paradigm for computing based on entropy functions and information gains. As indicated in the Equation, entropy calculates the degree of uncertainty in data. (3).Percentage of Binary Labels in the Data (p(r) is a binary label from 1 to 0). The information gain (I) shown in eq. may be used to compute the entropy difference between two data sets. (4). A subset of data is v.

$$F(G) = \sum_{j=1}^{n} -p(ri).log((rj)) \qquad (3)$$

$$J = F(G) - \sum_{k\epsilon E} p(u)F(u) \qquad (4)$$

Specifications and setup for the experiments include: One of the datasets used for training and testing will be DS1.

The SMFD dataset will include training and testing using fake face masks. The code for this dataset is DS2.

Training and testing stages will be integrated into one dataset, which will be known as DS3.

For testing, DS4 will get an LFW dataset with simulated face masks.

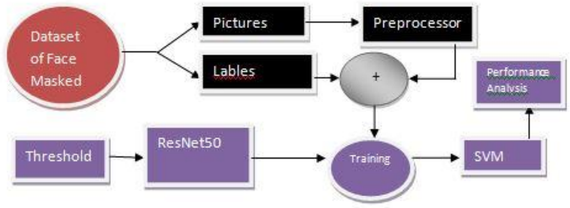


Fig. 3. Architecture

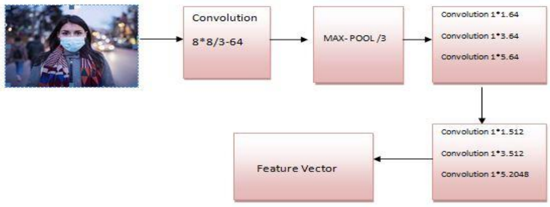


Fig. 4. Feature Extractor

In this study, performance matrices must be studied to evaluate the performance of different classifiers. Recall, Accuracy, and F1 Score [32] are the most typical performance metrics to be computed and are provided from Equations 5 and7.

$$Percision = \frac{TN+TP}{(TP+FP)} \qquad (5)$$

$$\text{Recollection} = \frac{TP}{(TP+FP)} \qquad (6)$$

$$\text{Score of F1} = \frac{Recollection \; *Percision}{(Percision \; +Recall\,)} \qquad (7)$$

The number of True Positive and False Positive samples and the number of True Negative and False Negative samples may be determined using a confusion matrix.Deep transfer learning was used in this study to increase picture classification accuracy however the results were unsatisfactory. A decision tree classifier and a support vector machine (SVM) classifier will each have their subsection, and the findings will be provided in five sub-sections. The ensemble classifier's findings will be presented in section three.The confusion matrices for the various classifiers will be shown in Section. Last is a comparison of test findings with those from other works, based on testing accuracy.

For the SVM classifier, researchers will repeat the same tests that were done with decision trees classifiers.SVM classifier validation accuracy and performance metrics are shown in Fig. 6 for each dataset.

As shown in Fig. 6, the SVM classifier beat the decision trees in all datasets. Validation accuracy for SVM in DS1 was 98% and 93.3 %, respectively. SVM classifiers outperformed decision trees in DS2 by a margin of 96 % to 100 %. DS3 tested both SVM and decision trees, and both scored %. SVM classifiers outperform decision tree classifiers in terms of validation accuracy and performance measures. As a last note, we achieved a 100% success rate in DS2 training, but only 98.7% in DS3 training for the decision trees classification.

The more photos in a dataset, the longer it takes to train an SVM classifier; hence DS3 takes longer to prepare because it has the most images out of all the datasets we've used so far. SVM classifiers are quicker than decision tree classifiers for all datasets. In the DS1 dataset, the SVM classifier was 0.29 seconds quicker than the decision tree classifier (improvement by 59 percent). The SVM classifier took 0.06% less time to classify data than decision trees in DS2 (edit by 68 %). Compared to decision trees, the SVM classifier in DS2 was 0.06s quicker.The DS3's SVM classifier outperformed the decision trees classifier by a factor of 0.06 s.SVM classifier accuracy and performance metrics are shown in Fig. 11 for each of the three decision tree testing processes stated in the decision tree classification section.

Fig. 5. Accuracy and Performance testing.

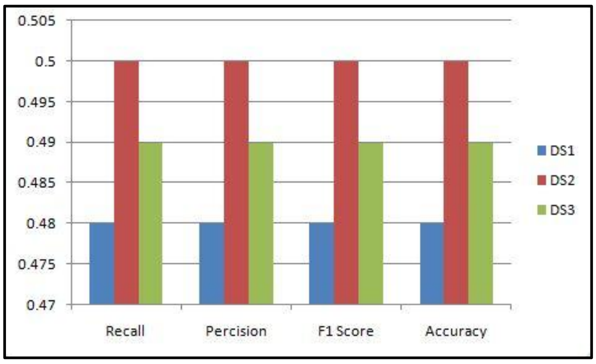


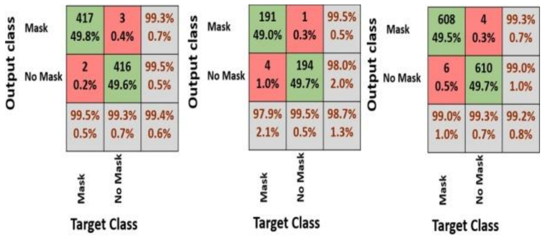
Fig. 6. SVM Classifier based Accuracy and Performance testing

It is shown in Figure 11 that (1) the SVM classifier's behaviour is equivalent to that of the decision trees classifier. The SVM classifier, on the other hand, is more accurate in its testing. While the SVM classifier was 82 % accurate in testing, the decision tree classifier was only % percent accurate in comparison. Decision trees produced accuracy rates of over 93% on the DS2 training set, while SVM classifier accuracy rates were above 97% for all datasets. The decision tree classifier had an accuracy of over 95%, whereas DS3 had an accuracy of over 98% for all datasets. When tested on DS4, the SVM classifier achieved a 99.9% accuracy rate, no matter whether DS1 through DS3 training datasets were used.

The SVM classifier beat out the decision tree classifier for accuracy, performance metrics, and time consumption in this area. With 99.4 % accuracy, DS1 was tested over DS3 throughout training. Training over DS2 yielded the best results, with a 99.49% success rate. Testing accuracy in DS4 was improved by training over DS3 with 100%, while training over DS3 with 99.19% resulted in the best results in DS3.

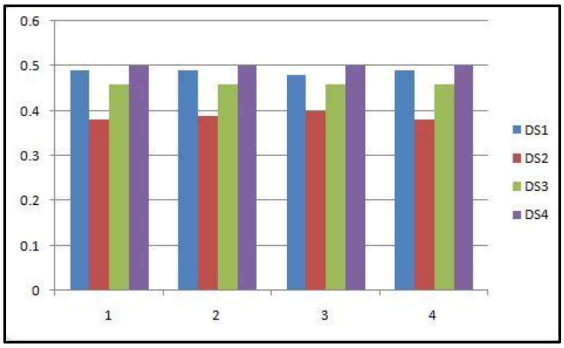
Work Comparison with existing works done

Masked datasets RMFD and LFW were utilised in this work, published in the journal PLoS One (DS2). They were able to get a 50% and 95% accuracy rate in their tests. The decision tree classifier had an accuracy of 93.44 %, while the ensemble classifier had an accuracy of 99.64 % in the provided research. When utilising the decision tree classifier, the testing accuracy is 99.76%, while using the SVM classifier, it is 100%.

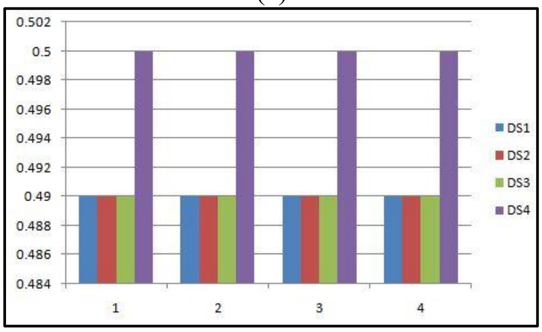


(a) (b) (c)

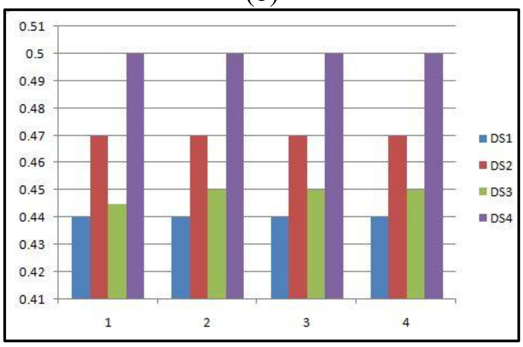
Fig. 7. Testingperformance metrics.



(a)



(b)



(c)

Fig. 8. DS1 DS2 and DS3 SVM classifier testing accuracy confusion matrices.

When DS3 was first tested, it was found to be inaccurate. Our accuracy for this dataset ranges from 96.50 to 99.35 % when using the SVM classifier. Using deep transfer learning models, we want to explore the masked face in a neutrosophic situation in the future.

IV. CONCLUSION:

The epidemic of COVID-19 coronavirus is wreaking havoc on the planet's health. There is a worldwide effort to fight viruses of this type. The World Health Organization considers COVID-19 protection a crucial countermeasure (WHO). A face mask detection hybrid model employs deep and traditional machine learning techniques. One and the other formed the model.Resnet50 was used in the first portion for feature extraction. In deep transfer learning, Resnet50 is a common model to use. Second, using standard machine learning techniques, we were able to identify masks worn by people. Such as decision trees, SVMs, and ensemble algorithms in the field of machine learning.

Various training and testing methods were used in this study, which involved using two datasets. The suggested model will be trained on a specific dataset before being tested on additional datasets to demonstrate its effectiveness. The SVM classifier was shown to be the most accurate with the least amount of training time. RMFD's SVM classifier was tested with a precision of99.64 %. A comparison study had been conducted with similar pieces. The model under consideration outperformed the existing ones in terms of testing precision. To yet, typical machine learning algorithms have been unable to achieve the greatest possible accuracy and speed at the same time. The neutrosophic domain may be used for feature extraction and classification and detection using deeper transfer learning models.

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