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Facial Mask Classification Using a Modified Deep Learning Transfer Model with Machine Learning Techniques During the Covid-19 Disease Outbreak

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Abstract
In response to the COVID-19 coronavirus disease, a worldwide health emergency has been declared. World Health Organization (WHO) recommends wearing face masks in public areas to protect against infectious diseases. The objective of this study is to present a conventional model that uses classical machine learning and deep learning to identify facial masks. Two features are included in the proposed model. A first part is designed to extract features using (Resnet50). For classifying facial masks, Support Vector Machines (SVM), ensembles, and decision trees are used. For this study, three face-masked datasets were selected. Three datasets have been developed: the Real-World Masked Face Dataset (RMFD), Labeled Faces Wild (LFW), and Simulated Masked Face Dataset (SMFD). In the case of RMFD, the (SVM) classifier achieved 99.5% precision, whereas the (LFW) classifier achieved 100% accuracy.

1. Introduction

The practice of covering a face in public places is growing as a result of the coronavirus epidemic worldwide (Chatterjee & Ahmad, 2021). Before spreading the coronavirus worldwide, Citizens Used to wear facial masks to shield their health from the toxicity of air. However, most are self-conscious about their appearance; they conceal their feelings from the community by covering their expressions (Mumtaz et al., 2021). Researchers have demonstrated that covering faces helps inhibit the spread of coronavirus. Coronavirus is a new widespread virus that has infected human health in the last millennium. In 2020, the accelerated dissemination of coronavirus prompted all humanity health organizations to declare coronavirus a universal epidemic. Over than six million cases of contaminated coronavirus in 188 countries in less than ten months (Ivorra et al., 2020). The virus is spreading to populated and overpopulated areas through close communication (Anirudh, 2020). The coronavirus pandemic has contributed to an extraordinary level of scientific collaboration worldwide (Kamal et al., 2021). The battle coronavirus, in many other ways, can benefit Artificial Intelligence (AI) focused on Deep Learning and Artificial Learning Techniques (Science et al., 2020). To simulate the transmission of coronavirus, to assist as a primary warning framework for possible epidemics, and to categorize susceptible communities, machine learning allows health care practitioners to evaluate vast amounts of data (Zhu et al., 2020). Support for advanced skills, along with neural networks, deep learning, and computer vision, to solve and anticipate novel syndromes is required to provide healthcare. The skill of AI is used to resolve the coronavirus epidemic (Fan et al., 2020), for example, coronavirus detection in clinical chest X-rays (Al-Lami et al., 2020), to help recognize the rate of infection and easily detect infections. Researchers face multiple challenges and risks when dealing with coronavirus distribution and transmission (Okuonghae & Omame, 2020). In several countries, the law obliges people to cover crowded areas. Generate detailed numerical data that can help predict possible outbreaks of coronavirus by authorities (zhou, 2020).

In this article, we proposed a method of facial mask recognition focused on deep transfer learning and traditional classifiers for machine learning. To avoid this, the recommended model should be paired with the surveillance cameras. Transmission of COVID-19 by enabling the recognition of persons who do not carry surgical masks. The integration of machine learning algorithms is a paradigm. For the retrieval of characteristics, we used deep learning and coupled it with a trio machine-learning algorithm. To determine the best fit algorithm that has attained the maximum efficiency and expended the minimum time in the preparation and identification procedure.

The novelty of this research is the use of the conceptual feature extraction framework of an end-to-end architecture with trio classifier machine-learning models for facial mask detection without traditional techniques.

2. Literature Review

Scientists and researchers have shown that the use of surgical masks tends to reduce the rate of coronavirus transmission (Eikenberry et al., 2020). (Qin & Li, 2020) proposed a new facemask wearing condition recognition system. Three types of facemasks wearing conditions were classified: right surgical mask wearing, wrong surgical mask wearing, and no surgical mask wearing. In the face detection process, the proposed technique achieved 98.70 percent precision. Principal Component Analysis PCA was applied to cover and uncover face recognition to identify the person (Ejaz et al., 2019). They reported that the precision of facial resonance using PCA is affected by the presence of masks. When the identified image is masked, the recognition accuracy decreases to less than 70 percent (Park et al., 2005). The authors proposed a technique to eliminate glasses from human frontal face images. The missing portion was retrieved through recursive error correction utilizing PCA restoration. An innovative GAN-based framework that can dynamically erase masks shielding the face region and recreate the image by constructing a damaged hole was proposed by (Ud Din et al., 2020). A full-face portrait that appears natural and practical is the output of the proposed model (Paredes et al., 2015), the authors provided a method to identify the appearance or absence of an obligatory surgical mask.

Medical professionals who do not wear surgical masks will receive alerts if they are not wearing their masks. The proposed system achieved 95% precision. An immersive process called MRGAN was proposed by (Khan et al., 2019). Based on obtaining the microphone area from the user and recovering this area using a Generative Adversarial Network. Deep learning was used to detect and recognize face emotions in real time (Hussain & Salim Abdallah Al Balushi, 2020). VGG-16 was used to classify the seven facial expressions. With 88 percent accuracy, the proposed model was trained on the KDEF dataset.

3. Features of Datasets

Experiments were performed using three initial datasets. The Real-World Masked Face Dataset (RMFD) (Wang et al., 2020) was the first dataset. One of the largest masked face datasets used in this study was developed by the author of (RMFD). 5000 masked faces and 90,000 unmasked faces were part of the (RMFD) dataset. Figure 1 shows samples of faces with and without masks. In this analysis, with a total of 10,000 photographs, 5000 images were used for faces with masks and without masks to match the dataset. A Simulated Masked Face Dataset (SMFD) (*GitHub - Prajnasb/Observations*, n.d.) is the second dataset. There were 1570 images in the (SMFD) dataset, 785 for virtual masked faces, and 785 for unmasked faces. Examples of (SMFD) images are shown in figure 2. The (SMFD) dataset for the phases of preparation, validation and testing.

Labeled Faces Wild (LFW) (LFW Face Database: Main, n.d.) was the third dataset used in this analysis. It is a virtual masked face dataset of 13,000 masked faces around a round for celebrities. Figure 3 illustrates examples of (LFW) images. For the testing process, the (LFW) dataset was used only as a benchmark testing dataset that was never trained by the proposed model.

4. The Suggested Model

The newly presented model consists of two primary parts: Deep transfer learning (ResNet50), such as a feature extractor, and traditional machine learning techniques, including support vector machine (SVM), ensemble, and decision trees. (ResNet-50) has produced superior outcomes when employed as a feature extractor (Khojasteh et al., 2019). The proposed traditional transfer-learning technique is illustrated in Fig. 4. The (ResNet-50) was primarily employed for the feature extraction step, with the training, validating, and assessment phases using the conventional machine learning approach. A deep learning approach that relies on residual learning is known as residual neural network (ResNet) (He et al., 2016). (ResNet-16), (ResNet-50), as well as (ResNet-101) are variants of (ResNet) designed to address the issue of disappearing gradients with a certain residual block. As illustrated in figure 5, (ResNet-50) has 50 layered deep, with a convolution layer at the beginning and a fully - connected layers at the end, surrounded by 16 blocks that represent residual bottlenecks, each of which has three levels of convolution layers. To enhance the effectiveness of our model in categorization, the final layer of (ResNet-50) was eliminated and substituted with three conventional machine learning models (ensemble, decision tree, and support vector machine (SVM)). The key focus of this research is the development of an ensemble, decision tree, and support vector machine (SVM) that does not overfit the training phase.

Figure 1. Image samples from the RMFD dataset.

Figure 2. Image samples from the SMFD dataset.

Wearing a Mask

Figure 3. Image samples from the LFW dataset.

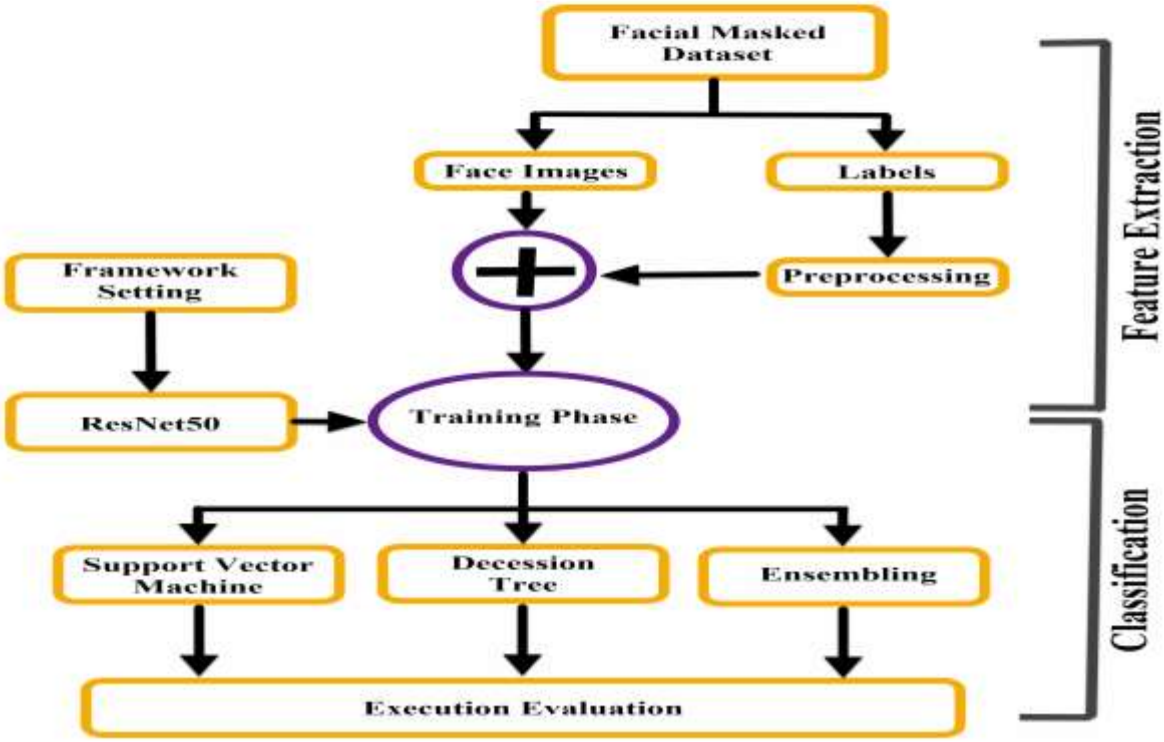

Figure 4. The proposed deep transfer learning

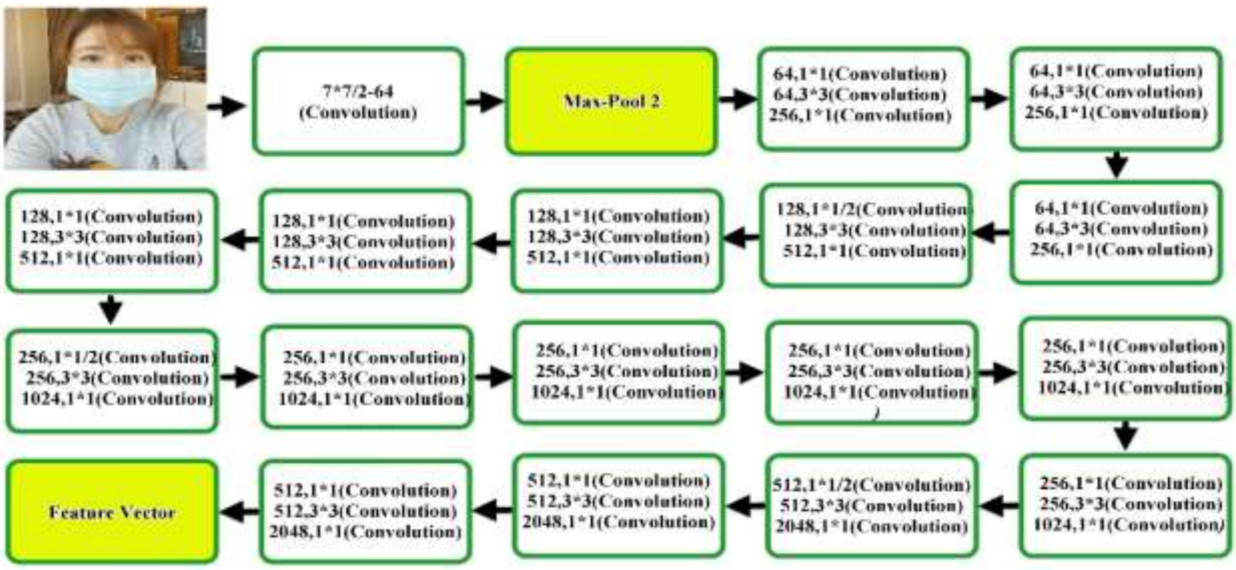

Figure 5. ResNet-50 proposed as the feature extraction algorithm.

4.1 Support Vector Machine (SVM)

A support vector machine (SVM) is one of the most widely used and well-known learning methods, along with associated classification models, for pattern classification and regression applications. (SVM) is a machine learning technique for classification that is dependent on the hinge functionality, as indicated in equation (1), while z is a labeling between 0 and 1, (w.I- b) is the outcome, w and b represent coefficients of classification purposes, and I is a vector of inputs. Equation (2) can be used to create the loss function that has to be reduced (Jogin et al., 2018).

$$h_j = \text{maximum}(\text{zero}, -z_j(I_j.w - b) + 1) \tag{1}$$

$$\text{Loss Function} = \frac{\sum_{i=1}^{n} \text{maximum}(\text{zero}, h_i)}{n} \tag{2}$$

4.2 Decision Tree

Classifier modeling of computing depends on the information gain, and the entropy function is the decision tree. The degree of uncertainty in the data is calculated using entropy, as indicated in equation (3). D refers to existing data, q is a binary label ranging from 0 to 1, and p(x) represents the proportion of the q label. Then, we evaluated the information gain (I), as demonstrated in equation (4), to figure out the variation in entropy as from data. v would be a subset of the dataset (Navada et al., 2011).

$$E(D) = -\sum_{i=1}^{m} \log\,(p(q_i) \times p(q_i) \tag{3}$$

$$I + \sum_{v \in D} E(v) \times p(v) = E(D) \tag{4}$$

4.3 Ensemble Techniques

Machine-learning approaches, known as ensemble techniques, produce a group of classifiers. A ‘classifiers ensemble’ is a group of classifiers whereby independent decisions are combined in some method to recognize training examples, often through weighted or unweighted scoring (Polikar, 2012). Ensemble approaches were employed using Logistic Regression (Kleinbaum & Klein, 2010), Linear Regression (Naseem et al., 2010), and the K-Nearest Neighbors (k-NN) technique (Mangalova & Agafonov, 2014). The phases of the ensemble method are as follows:

I. Create M classifiers
II. Develop each classifier independently
III. Combined M classifiers and averaged the respective results.

As shown in Eq. (5) (Xiao et al., 2018), the ensemble is enhanced by utilizing a complex weight (α) to achieve extraordinary outcomes.

$$\bar{z} = \sum_{i=1}^{M} z_i \propto_i \tag{5}$$

5. Experimentation Outcomes

On a computing network with an Intel Xeon W-2295 3.0GHz and 256GB DDR4-3200 MHz RDIMM Memory + 512GB NVMe PCIe SSD + 8TB 3.5-inch 7200RPM SATA HDD, all the research experiments were carried out. Throughout this study, various testing trials were conducted using PYTHON software. The configuration and specifications used in the experimental trials were as follows:

- The following three classifiers were used.

I. Support Vector Machine (SVM)
II. Ensemble
III. Decision trees

- Dataset 1 (DS1) is given RMFD data with realistic surgical masks for (testing and training stages).
- DataSet 2 (DS2) is given SMFD data with artificial surgical masks for (testing and training stages).
- For the training and testing phases, merged data containing Dataset 1 (DS1) and Dataset 2 (DS2) were referred to as Dataset 3 (DS3).
- Dataset 4 (DS4) is the given data of LFW containing simulated surgical masks during (testing).
- The types of data were divided as follows: 10 percent for the validation stage, 70 percent for the training stage, and 20 percent for the testing stage.

Performance matrices must be explored in this research to assess the effectiveness of various classifiers. Recall, Precision, Accuracy and F1 Score (Goutte & Gaussier, 2005) represent the most frequently computed key parameters, which are shown in equations (6)– (9).

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \tag{6}$$

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}} \tag{7}$$

$$\text{Accuracy} = \frac{\text{True Negative (TN)} + \text{True Positive (TP)}}{\text{True Negative (TN)} + \text{False Negative (FN)} + \text{True Positive (TP)} + \text{False Positive (FP)}} \tag{8}$$

$$\text{F1 Score} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (9)$$

where (FP) is the number of false positive cases, (FN) is the number of false negative cases, (TP) is the number of true positive cases, (TN) is the number of true negative cases, (TP) is the number of true positive cases from a confusion matrix. Deep transfer learning was used in this study to enhance image classification performance; however, the findings were unsatisfactory. These experimental findings will be provided in five subcategories, the first of which will discuss the findings acquired with the decision tree classification algorithm, and the second of which will explain the findings with the support vector machine (SVM) classifier. The ensemble classifier's findings are presented in subcategory number three. The confusion matrices for the various classifiers are shown in subcategory number four. The fifth part will demonstrate a comparison of the outcomes with similar studies in light of testing precision.

5.1 Metrics of Decision Trees Classifier Performance, Testing Accuracy, and Validation

Three datasets (DS1, DS2, and DS3), which were described previously in the experimental procedure, were used for training, validation, and testing. Only testing will be done on the (DS4.) In the validation stage, the findings generated by the decision tree classifier for the various datasets are shown in figure (6).

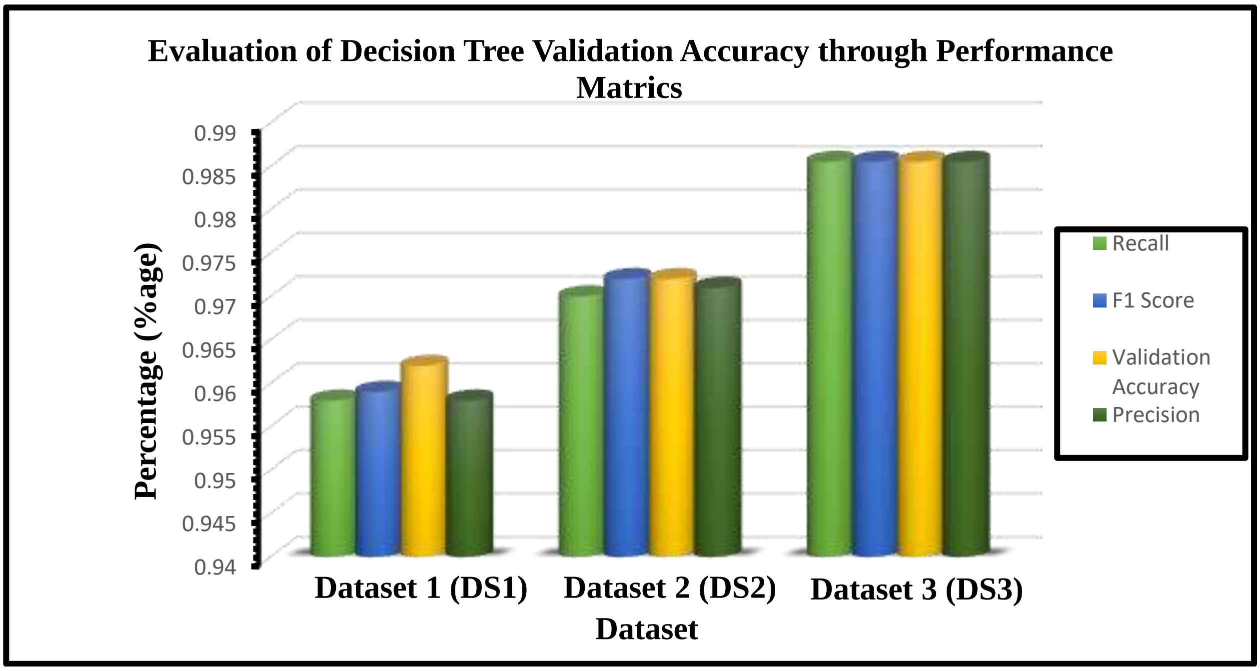

Figure 6. Validation of decision tree classifiers with different datasets, accompanied by performance metrics.

The decision tree classifier reached an accurate validation for DS1, exhibiting results that varied from 95% to 96%. DS1 has actual masks with various facial expressions, including various face mask varieties. Furthermore, the decision tree classifier under DS2 obtained a validation accuracy of 97% using performance metrics. DS2 contained images of genuine individuals with fake masks. In DS3, the decision tree classifier obtained a validation accuracy of 98.5% using performance measures. DS3 is a set of data that combines DS1 and DS2. DS3 represents an immense database in terms of image count, which aids in gaining higher accuracy, and a greater amount of data implies greater precision in the application of machine learning. While the time taken is relative from machine to machine, this provides a decent measure of the effectiveness of the classifier. Figure 7 depicts the time the decision tree classifier spent throughout the training procedure for various data.

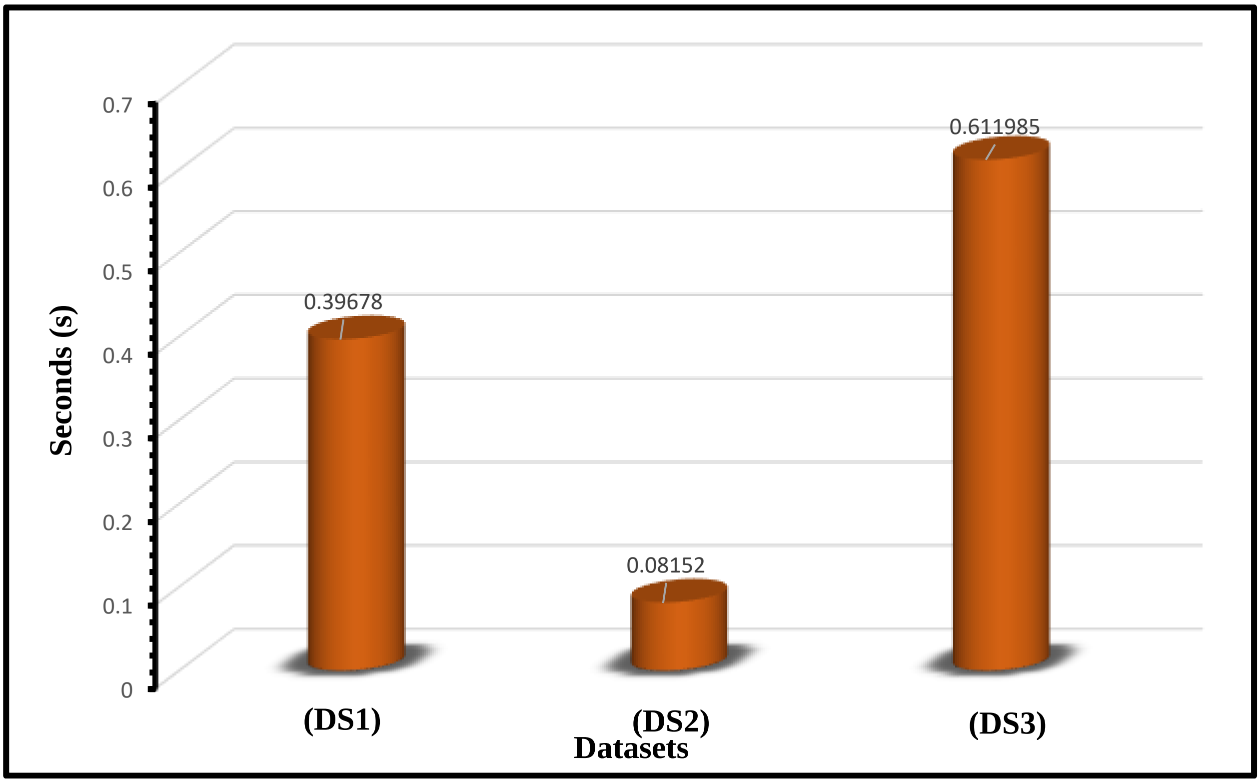

Figure 7. Time consumed in training the decision trees classifier using various datasets.

The time consumed is proportional to the amount of dataset and the abilities of the machine being used. The number of images is presented in the database attribute section. Various testing procedures were used in this study to assess the effectiveness of the decision tree classifier, which are presented below:

I. Training on data set DS1, followed by testing on DS1, DS2, DS3, along with DS4.
II. Training on data set DS2, followed by testing on DS1, DS2, DS3, along with DS4.
III. Training on data set DS3, followed by testing on DS1, DS2, DS3, along with DS4.

Figure 8 depicts the percentage attained for testing the precision and efficacy indicators for the various testing procedures of the decision-tree classifier.

Figure 8. The accuracy of the decision tree classifier is tested with different testing strategies using performance metrics.

I. During the training throughout DS1, the decision tree classifier fails to achieve a satisfactory classification accuracy of 37% in DS2 because DS2 has an excessive variance of fabricated face masks. This will also be observed in DS3, a merged database from DS1 and DS2.
II. When trained on DS2, the decision tree classifier achieved 94% accuracy over DS1, which included genuine masks.
III. In all datasets, the decision tree classifier scored the maximum precision with the performance metrics when trained on DS3. More than 97% of the findings were obtained.
IV. DS4, which was only utilized for testing that was not previously instructed on, the decision tree classifier obtained an accuracy level of 99.95% regardless of whether training was performed on DS1, DS2, or DS3.

From this part, we can infer that the decision tree classifier attained the best precision attainable when trained on DS3. The greatest testing accuracy was 97.56% for DS1, 97.64% for DS2, 97.95% for DS3, and 99.95% for DS4.

5.2 Metrics of SVM Classifier Performance, Testing Accuracy, and Validation

The SVM classifier was subjected to identical trials of experimentation as the decision tree classifiers. The validation accuracy and precision metrics of the SVM classifier across various sets of data are shown in Fig. 9.

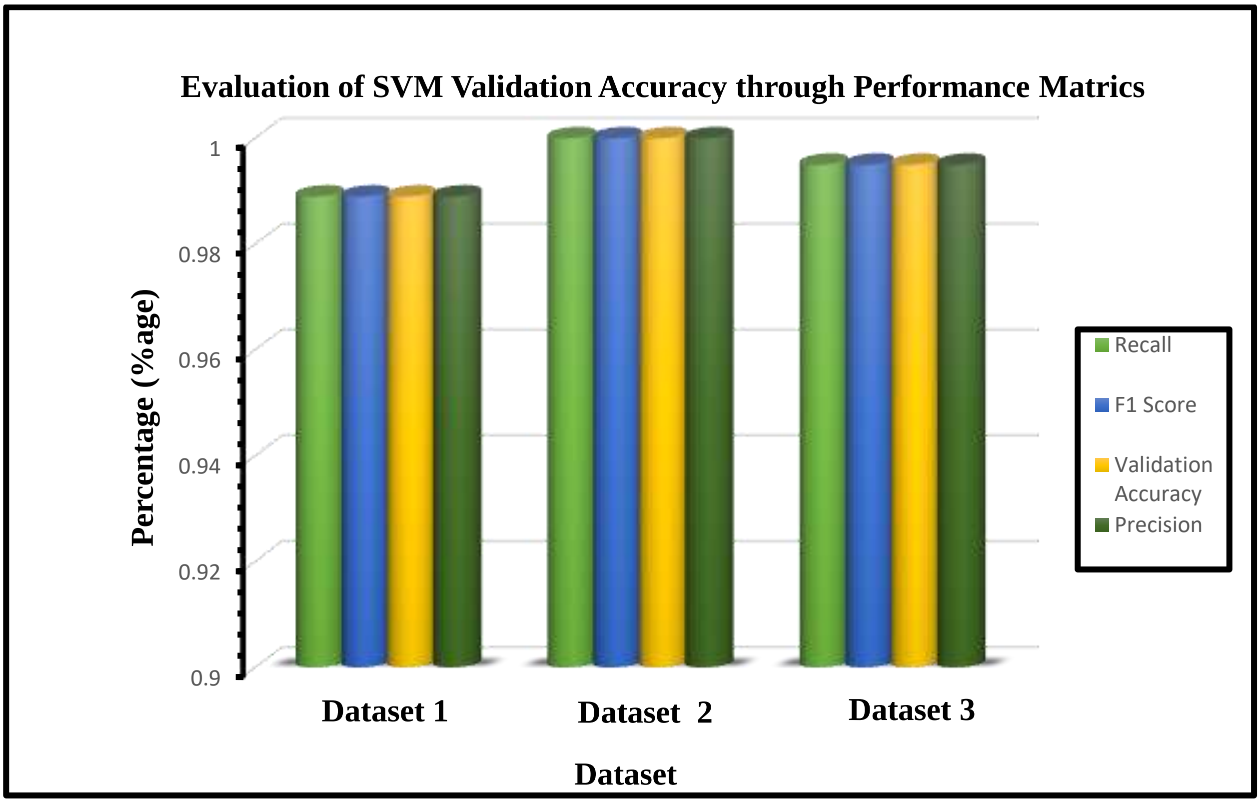

Figure 9. Validation of SVM classifiers with different datasets, accompanied by performance metrics.

Figure 9 indicates that the SVM classifier outperformed the decision tree classifier in terms of validation accuracy across every set of data. For DS1, SVM achieved more than 98% validation precision, whereas decision trees achieved 95% to 96% precision. The SVM classifier scored 100% for DS2, whereas the decision trees scored 97%. The SVM earned 99.5% in DS3, whereas decision trees gained 98.5%. The SVM classifier consistently leads the decision tree classifier in terms of validation precision and performance metrics. Another noteworthy point is that training for DS2 attained the greatest validation precision achievable with an accuracy of 100%; however, the best validation precision in the decision tree classifier was 98.5% in DS3.
The time spent by the SVM classifier on various sets of data is also an important consideration when assessing its accuracy, as indicated in figure 10.
Applying the SVM classifier, the greater the amount of data, the greater the amount of time the classifier will need to spend. Because DS3 has the greatest number of images compared with the presented datasets, it takes longer to train. It is worth noting that the SVM classifier consumes less time than the decision tree classifier on all sets of data. In DS1, the SVM classifier used 0.29s less time than the decision tree classifier. For DS2, the SVM classifier required 0.059s for a smaller amount of time than the decision tree classifier. For DS3, the SVM classifier required 0.374s for a much shorter time than the decision tree classifier.

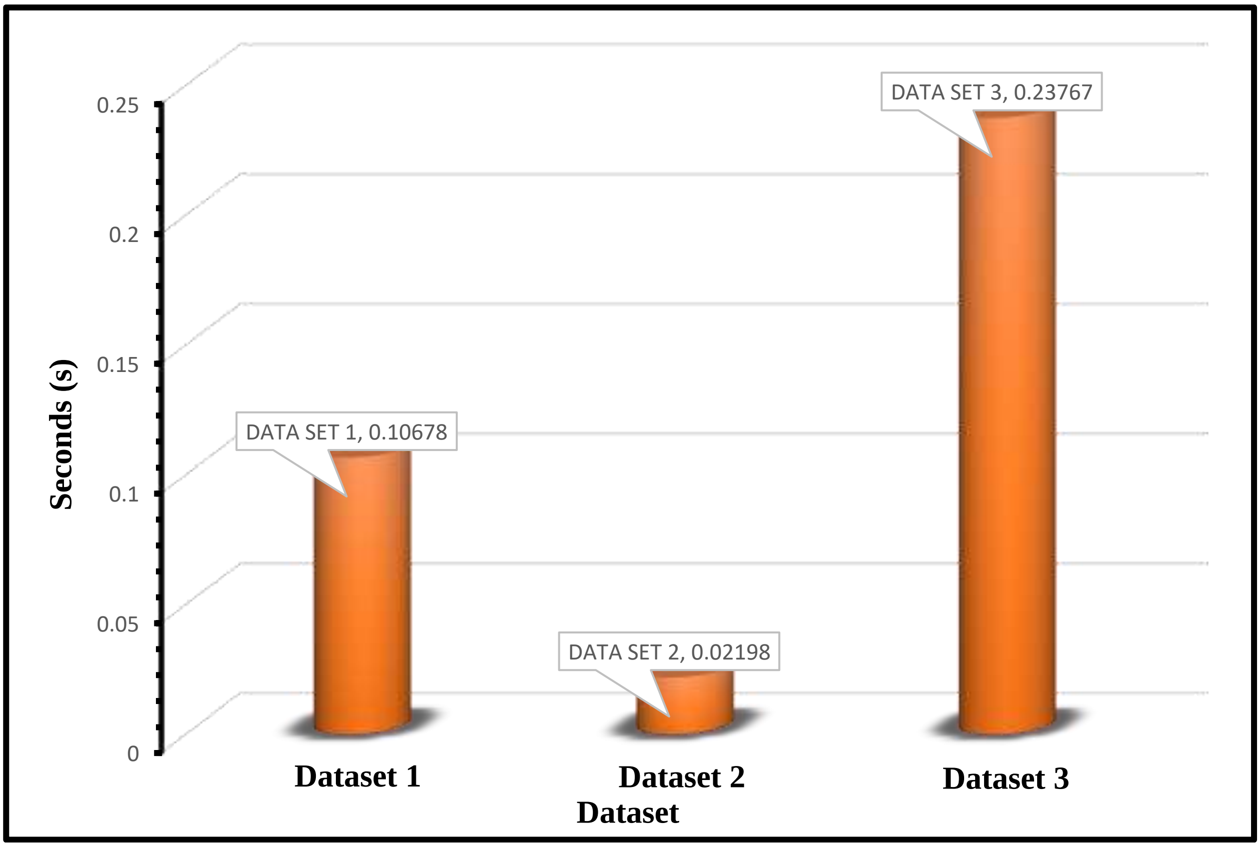

Figure 10. Time consumed in training the SVM classifier using various datasets.

Based on the various testing procedures in the decision tree classifier portion, Figure 11 displays the percentage attained for testing precision and efficacy metrics from the SVM classifiers.

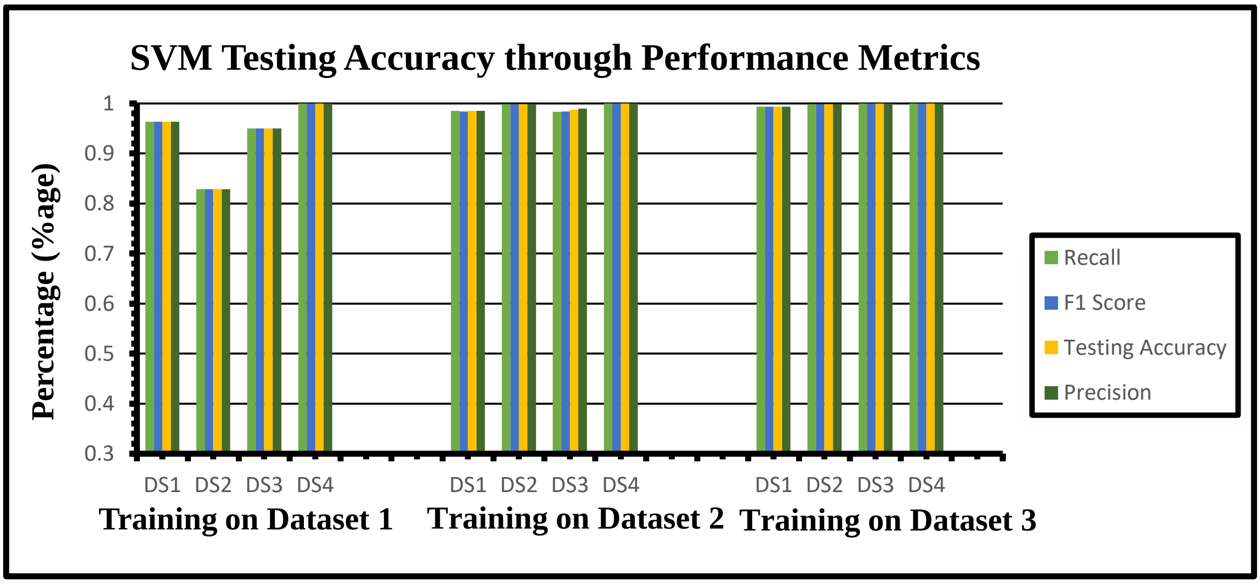

Figure 11. The accuracy of the SVM classifier tested with different testing strategies using performance metrics.

Decision tree classifiers and SVM classifiers exhibit similar characteristics; however, SVM classifiers achieve greater accuracy in accuracy tests, as shown in figure 11.

I. As a result of training with DS1, the SVM classifier obtained an 82.89% testing accuracy over DS2, whereas the decision tree classifier obtained a 37% accuracy.
II. A decision tree classifier reaches greater than 96% accuracy when trained on DS2, whereas the SVM classifier achieves greater than 99.8% accuracy on DS2.
III. With DS3, SVMs had an average accuracy of over 99% for all datasets, whereas decision trees had an average accuracy of over 97%.

Regardless of whether training was performed on DS1, DS2, or DS3, the SVM classifier obtained almost 100% accuracy on DS4, which was exclusively used for testing. In our analysis, we concluded that the SVM classifier performed better in terms of validation, testing accuracy, performance metrics, and time spent than the decision tree classifier.

Training over DS3 yielded the maximum accuracy of 99.33% for DS1. Training over DS2 yielded the maximum accuracy of 99.89% for DS2. Training over DS3 yielded the best accuracy of 99.98% in DS3, and training over DS3 yielded the maximum testing accuracy of 100% in DS4.

5.3 Metrics of Ensemble Classifier Performance, Testing Accuracy, and Validation

The ensemble classifier will be tested using the same experimental procedures as the decision trees and SVM classifiers. Figure 12 illustrates the validation performance and validation accuracy metrics associated with the ensemble classifier on several datasets.

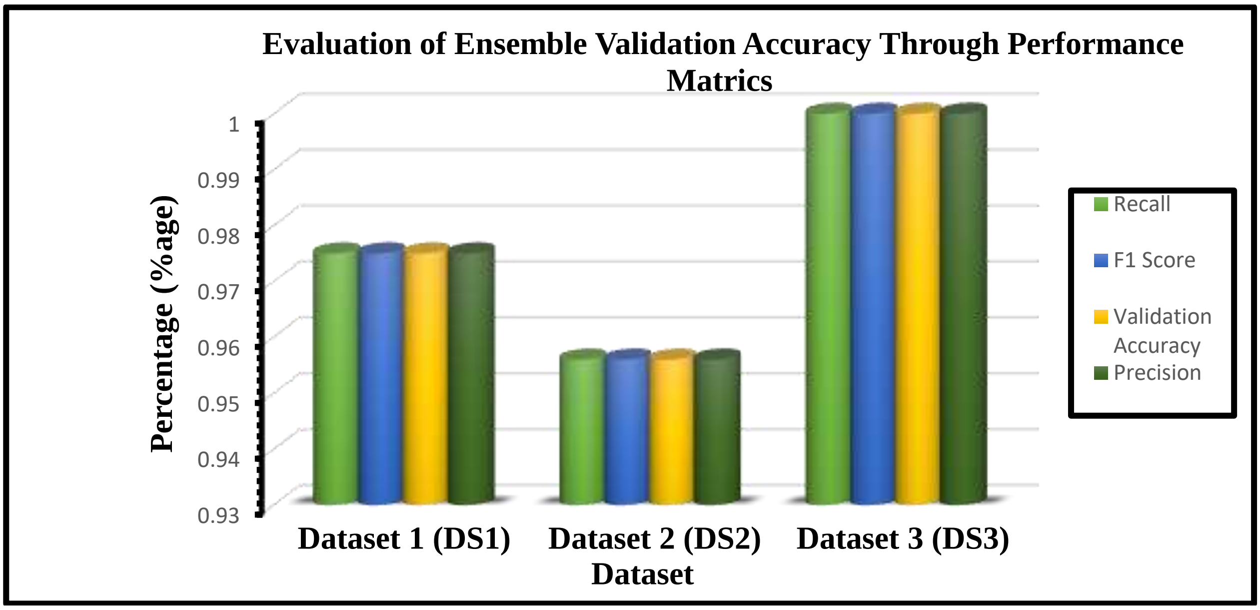

Figure 12. Validation Ensemble classifiers with different datasets, accompanied by performance metrics.

Figure 12 demonstrates that the ensemble classifier obtains the maximum accuracy when there is additional data available for training. The ensemble classifier obtained 100% testing accuracy for DS3. It beat the decision tree and SVM classifier. In DS2, the SVM earned the greatest validation accuracy of 100%, while the ensemble classifier reached 95%. In DS1, the SVM got the greatest validation accuracy (98.9%), while the ensemble classifier reached 97.5%.

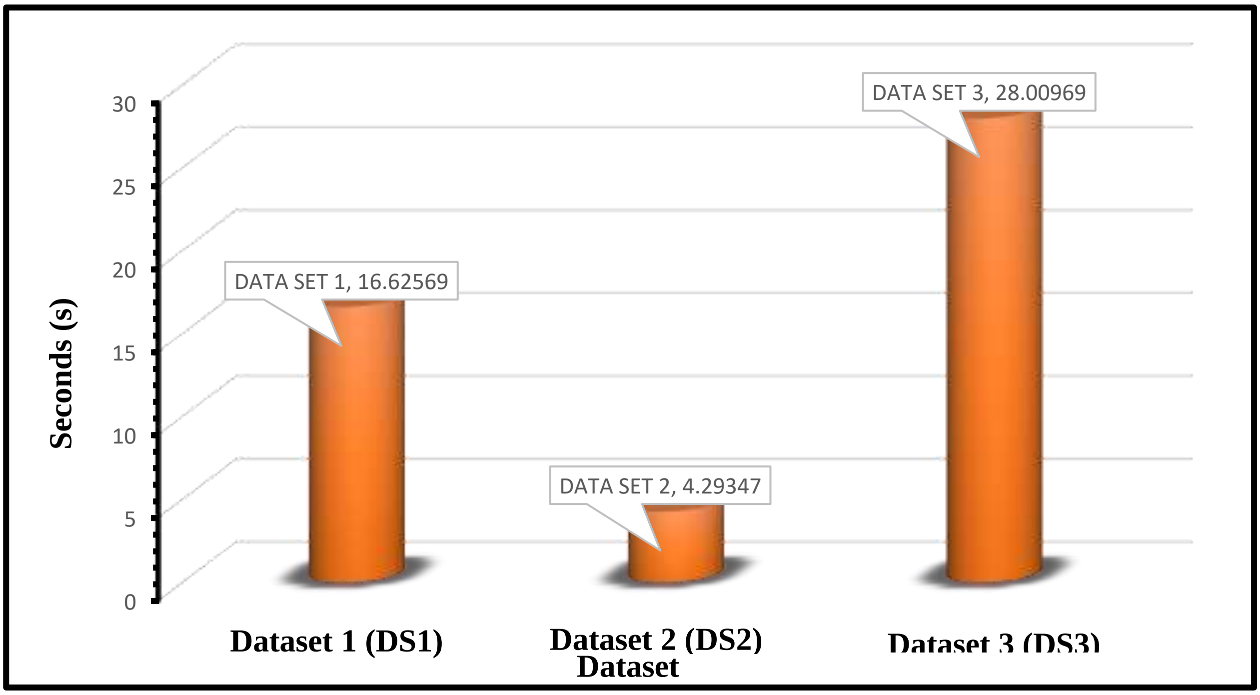

Figure 13. Time consumed in training the Ensemble classifier using various datasets.

Figure 13 depicts the time required during the ensemble classifier's training procedure. Figure 13 clearly illustrates that the ensemble consumes additional time than SVM classifier and the decision tree. The DS3 training duration was 28.00 seconds, whereas the decision tree and SVM classifiers took 0.61198 and 0.2376 seconds, accordingly. Based on the findings obtained, we can infer that the ensemble classifier's efficiency in terms of implemented time is not effective significantly. The reason is caused by the ensemble classifier's characteristic of trying all potential classifiers with the maximum accuracy, thus by default takes a lengthy time when compared to various classifiers.

Figure 14 illustrate the proportion of ensemble classifiers that are accurate and perform well according to the various testing procedures described in the segment on decision trees classifiers.

I. In training, the ensemble classifier performed better than the SVM classifier on DS1, achieving 99.88%, 89.32%, 97.01%, and 99.98% for DS1, DS2, DS3, and DS4, respectively. For DS1, DS2, DS3, and DS4, the SVM classifier scored 96.32%, 82.89%, 94.99%, and 100%, respectively.
II. During DS2 testing, the SVM classifier outperformed the ensemble classifier.
III. As a result of DS3 training, the ensemble classifier scored 99.76%, 99.64%, 99.15%, and 100%, respectively, as compared to the SVM classifier. For DS1, DS2, DS3, and DS4, the SVM classifier scored 99.33%, 98.88%, 99.99%, and 100%.
IV. Despite not having been trained on DS1, DS2, or DS3, the ensemble classifier achieved more than 99% accuracy on the DS4, which is solely used for testing. The ensemble classifier beat the SVM classifier in terms of testing accuracy across all training techniques.

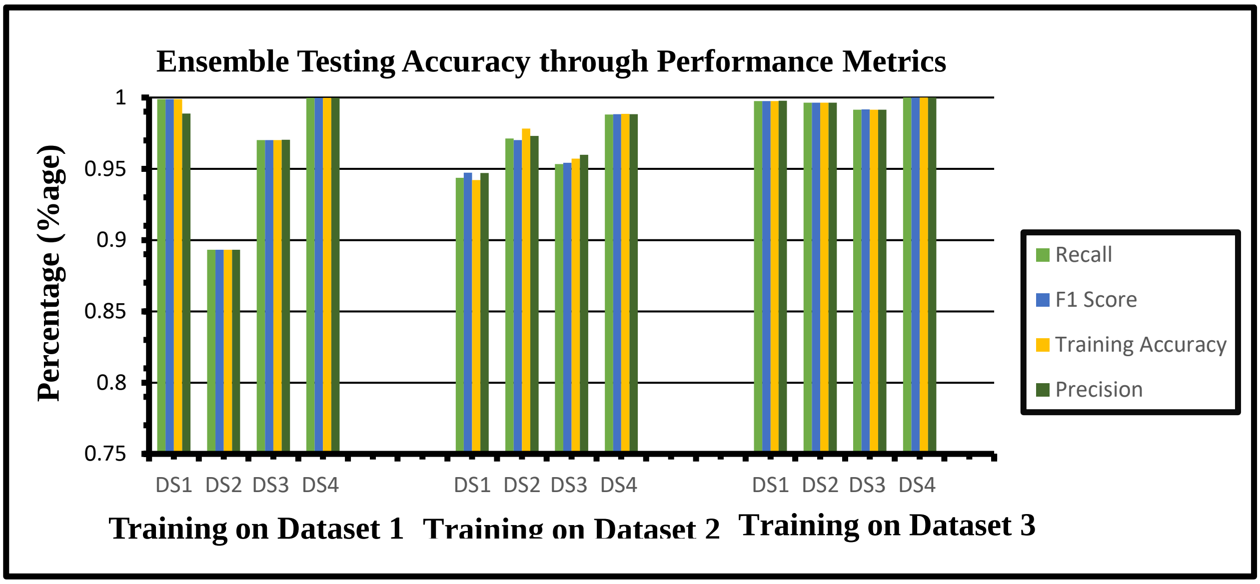

Figure 14. The accuracy of the ensemble classifier tested with different testing strategies using performance metrics.

The ensemble classifier is likely to outperform decision trees and SVM classifiers in terms of validation, testing accuracy, and performance metrics while training on DS1 and DS3. SVMs, however, outperform other classifiers when trained across DS2. SVM classifiers also require the least training time.

5.4 Class Accuracy of SVMs and Ensemble Classifiers Based on Confusion Matrix

Confusion matrices provide additional information regarding the classifier's performance. Training across integrated datasets (DS3) is the best way to acquire the maximum potential accuracy for the various classifiers. In terms of decision trees, confusion matrices are excluded since they achieved the lowest testing accuracy. As can be seen in Figure 15, the confusion matrices for SVM classifiers for DS1, DS2, and DS3 are shown during the training process while DS3 is used as the test dataset. The gained testing accuracy is 99.6% for DS1, 98.9% for DS2, and 99.4% for DS3. When training on DS3, the ensemble classifier's confusion matrix is shown in figure 15 for DS1, DS2, and DS3.

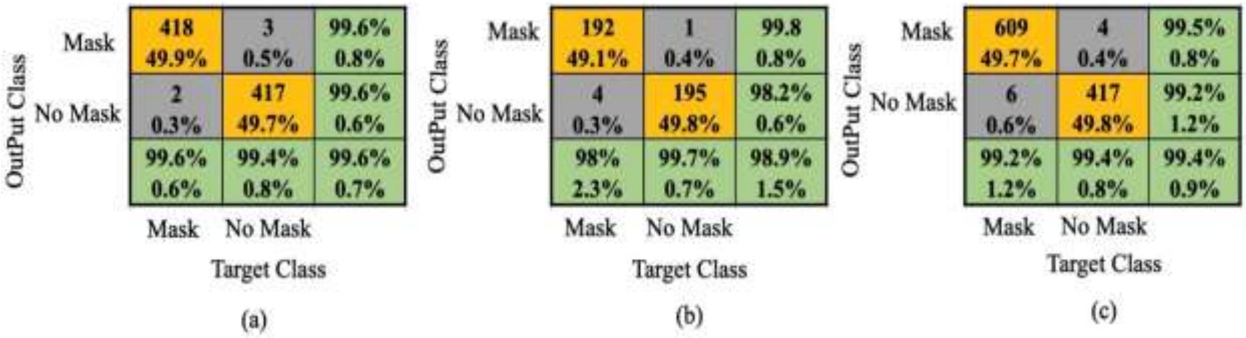

Figure 15. The confusion matrix shows the testing accuracy for (a) DS1, (b) DS2, and (c) DS3 using the SVM classifier after training.

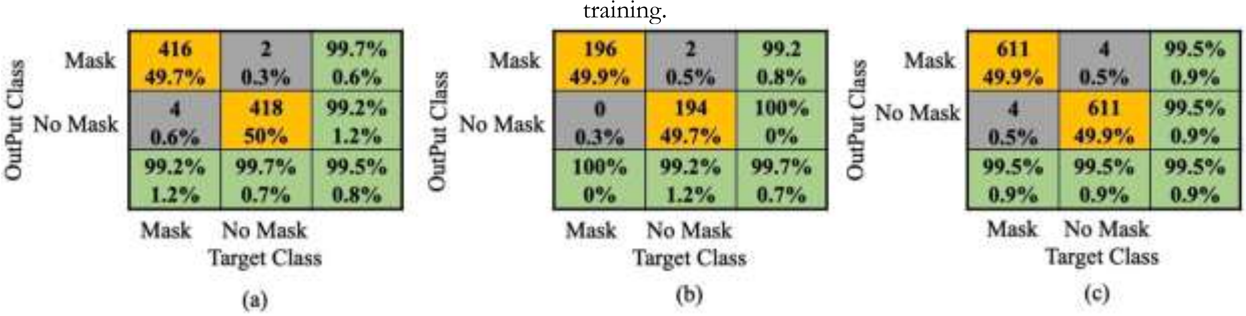

Figure 16. The confusion matrix shows the testing accuracy for (a) DS1, (b) DS2, and (c) DS3 using the Ensemble classifier after training.

The obtained testing accuracy is 99.5% for DS1, 99.7% for DS2, and 99.5% for DS3 as shown in figure 16. There is no difference in the confusion matrix for DS4 between SVM and ensemble classifiers, having 100% testing accuracy. Because the SVM classifier produced very similar results to the ensemble classifier, the study chose the SVM classifier for the following reasons:

I. SVM and ensemble classifier accuracy scores for DS3 training are quite similar, with just a 0.01% difference.
II. Over the training of DS3, the SVM classifier achieved 100% accuracy in testing DS4.
III. Compared to other performance metrics, SVM classifiers require less training time.

6 Conclusions and Future Research

This study introduced a hybrid model for face mask identification that combines deep and traditional machine learning. There were two components to the suggested model. The initial phase was using Resnet50 to extract features. One of the most often used models in deep transfer learning is Resnet50. The identification of face masks using traditional machine learning techniques was the focus of the second section. Traditional machine learning techniques such as ensemble algorithms, decision trees, and Support Vector Machines (SVM) were chosen for study.

This study experimented with three different data sets and used various training and testing methodologies. To demonstrate the effectiveness of the suggested model, the strategies allow for testing on several datasets while training on a particular dataset. SVM classifiers were found to have the highest accuracy and the least training time according to the research provided. Testing accuracy of the SVM classifier in RMFD was 99.95%. For LFW, it achieved 100% accuracy and for SMFD, it achieved 99.85% accuracy.

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