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MASKED FACE RECOGNITION BASED ON FaceNet PRE-TRAINED MODEL

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Abstract

COVID-19 has been spread throughout the world during last three years. Consequently, daily life applications are adapted into a life where existence of the virus is taken into account. Wearing facemasks is one of the major adaptations we apply. The virus can transmit by touch and infected materials. For biometric or security systems, recognition and identification techniques obligate the touch of devices, which make coronavirus spreads rapidly. Therefore, face recognition is one of the efficient solutions to handle biometric or security systems and avoid touching devices. Wearing a facemask decreases the spread of the virus. Apart from corona virus, fraud and robbers which wearing special masks to be unknown, and nose covering for cold regions. However, when wearing masks, face recognition techniques will not get desired results because of masking the important regions of the face that allow the identification, such as the nose, and the mouth. The face masking is the well-defined facial occlusion problem nowadays. Researchers still make it a challenge to tackle using several techniques such as matching approach, restoration method, Discard Occlusion based method, and Convolutional Neural Network Techniques that are based on hard training. Moreover, the principal aim of this paper is to recognize faces that wear masks using an efficient approach based on deep convolutional neural network, which is the FaceNet, to recognize faces that are wearing masks and predict its names using well-known datasets. Overall, the system achieves acceptable rates for the face recognition problem where the test faces are masked.

Keywords: Covid-19, convolutional neural network, face recognition, masked face, machine learning.

INTRODUCTION

Nowadays, coronavirus is the most discussed problem globally, which is the most dangerous virus when it spreads. It spreads through contact, shaking hands, or any other connection. Moreover, all this has become a problem now, as people need to return to their life, and get rid of this deadly virus.

To reduce its spread, it is essential to stay away from all its causes and apply coronavirus preventions, i.e., wearing a special mask and gloves. A fundamental question in this study of covid-19 spread is the problem of security and biometrics, such as identification by fingerprint, password. So all this led to thinking about face recognition technology as a suggested solution to avoid the connection with people and the spread of coronavirus.

Based on these findings, we must study the situation from all sides. For example, as we know, the face made of the eyes, the nose, and the mouth. This medical mask will cover the nose and mouth to limit the spread of infection. The mouth and nose are the most important features of the face. Face recognition systems are based on them to calculate the distance, the widths, and the lengths for the processing of matching. It is of great interest to study whether the engineering side will handle the problem of biometrics and security during the pandemic or it could handle it even after this period (Terrance E. Boult, 2009).

Particularly after the beginning of Deep-Fake technologies in 2019, when robberies with a mask began to spread, concerns about technologies for recognition of the face and the dangerous potential they could have. A young Russian man was able to create an algorithm, which could suggest that cosmetics were used to certain effects, which could trick face recognition algorithms. In order to deceive surveillance systems, a young German also invented a device to sew fabric to wear on this face so that he was carrying a shawl, which clothes his lip and eye drawings.

We propose to illustrate the literature review by face recognition systems and masked face recognition system and their historical development. Then, we have to clarify each theoretical side of the tools and the approaches that are used in our proposed method. After that, we will explain the proposed method by giving an overview, the different splits of the datasets, the steps of the pipeline, and the evaluation methods. Finally, we have proposed four scenarios based on a deep convolutional neural network to recognize which contains masked faces and unmasked faces. Those scenarios help us to choose an efficient approach. Unmasked and Non-masked faces are using to extract features from it. The nose and mouth are predictable regions, which help us to get efficient occlusion results later. The choice of the efficient scenario is based on the Evaluation and the accuracy percentages.

LITERATURE REVIEW

The historical development of face recognition and masked face recognition technique, help us to compare and understand the difference between the two systems.

FACE RECOGNITION APPROACHES

To recognize the identification of certain things, a system needs reliability. The goal is to ensure that only an authorized user and not others access the System. The physiological and/or behavioral properties of people are in focus. That System includes four methods to detect the authorized user, which are as follows.

KNOWLEDGE-BASED METHODS

Knowledge-based methods use the principle of encoding human faces. These methods are based on some rules to translate our knowledge of faces into a set of fundamentals to guess. A face, for example, usually has two symmetrical eyes, and the area of one eye is darker. The distance between the eyes or the severity of the color difference could be the characteristic face of the eye area and the bottom region. The main problem is the difficulty of developing an appropriate set of rules. If the restrictions were too vague, there might be numerous false positives. On the contrary, if the restrictions were excessively specific, there may be numerous false negatives. One possibility is to develop hierarchical techniques of knowledge to solve these issues. With basic input, these basic strategies are effective. But if the man wears spectacles, what happens? This problem can be addressed by other features. For example, algorithms recognize face-like textures or human skin colors (Solanki Kamini, 2016).

FEATURE–INVARIANT METHODS

Feature invariant strategies that attempt, in spite of its angle or location, to discover invariant facial characteristics. Facial recognition employs distinguishing facial characteristics, including mouth, nose, eye, lips, and elements such as mouth, forehead, ears, high eye outlines, the zones, and the gap between the eyes, nose longitude, and mandibular angle (Solanki Kamini, 2016).

TEMPLATE-MATCHING METHODS

Those programs define data photos using recorded facial or functional patterns. Matching templates attempt to try to quantify a visage as a service. A typical format can be found for every feature. All faces individually, many characteristics may be defined. For instance, the facial counter can be separated into eyes, mouth, and nose edges can also be constructed as a facial model but that is a matter of fact. Most approaches are confined to frontal faces. A face can be expressed as a form too. Various designs employ the light and darkness relationship between facial areas. Compared to the input, these conventional motifs detect recognitions pictures. This technique is easy to use, but for facial detection, it is inadequate. It cannot go well results with attitude, size, and structure modifications. Nevertheless, to solve these issues, deformable templates were presented (Solanki Kamini, 2016) (Kuldeep Singh Sodhi, 2013).

APPERANCE-BASED METHODS

A replicating templates, which the pattern foundation is drowned from series of pictures. In general, appearance-based methods strategies rely on statistical analytical approaches and machine learning to find the facial features pictures.

MASKED FACE RECOGNITION APPROCHES

Occlusion is a major contain for 2D face recognition techniques in the real world. It usually comes out of the use of hats, lenses, masks, and anything else that might hide part of the face while leaving others unaltered. The most difficult task for facial occlusion is thus to wear masks since it occurs in a large section of the face including, the nose. This difficulty was dealt with in several ways. We may divide it into three categories: local matching approach, restoration approach, and discard occlusion based approach.

MATCHING APPROACH

It aims to compare the similarity in a matching process between photos. In general, a number of patches of the same size are sampled in the facial picture. Each patch will then be extracted from the feature. In conclusion, the method of matching sample and gallery is applied. The benefit is that the sample method patches do not overlap, therefore preventing the effect on other informative sections by blocked region.

Rather than just the corresponding points, other approaches identity key points in the facial picture. For this work, the key point was initially discovered, and their textured and geometrical characteristics were extracted. Next, the matching of the point is done to match the feature obtained (HARIRI, 2020).

Finally, by the distance between the two aligned sets, the resemblance of two faces is achieved. To choose the proper key points, the sift keyboard descriptor is used. Gabor ternary pattern and point set matching will then be performed for partial face recognition with the local key points (HARIRI, 2020).

RESTORATION APPROACH

According to the gallery, the occulted portions in the sample faces are restored here. The occlusive areas are detected by threshing the 3D image profound map values. The main component analysis is then carried out (PCA) (Kuldeep Singh Sodhi, 2013). Several techniques rely on the assessment of the occluded areas. The iteration close point (ICP) technique was utilized. A curve is used to control the occluded regions using a statistical estimate of the curve. Partly observed curves are completed using the PCA- technical curve model (HARIRI, 2020).

DISCARD OCCLUSION BASED METHOD

These techniques try to recognize areas detected in the face picture and remove them from the extraction of features and classification process totally to avoid a mistaken reconstruction process. The segmented technique is one of the greatest approaches for initially detecting and using the occulted region in the next phases, just the non-included section. The global masked screening was used to eliminate the obstructed zones. Next to the restoration, the partial guppy PCA with convectors (Kuldeep Singh Sodhi, 2013). A partial matching approach has also been implemented to efficiently delete the occluded part and then use the non-occluded areas process of correspondence (HARIRI, 2020).

Deep CNNs have become a widespread technique to face recognition with the release of AlexNet architecture in 2012 (Wu, 2017). It has also been employed successfully under occlusion in face recognition. The fact that the human visual System automatically disregards the areas which are occluded is the basis of deep Learning and concentrates only on those that are not occluded to remove the masked region feature component for the recognition procedure.

METHODS

The proposed method is based on five steps. The split dataset into train and validation datasets (mixed and normal). Then, masked face detection and extraction (with landmarks estimation). After that, we have to create face embedding to classify them with an efficient classifier to predict the names. Finally, we have to evaluate the result using evaluation metrics. The following diagram (is shown in Figure 1.) is an overview of the proposed method.

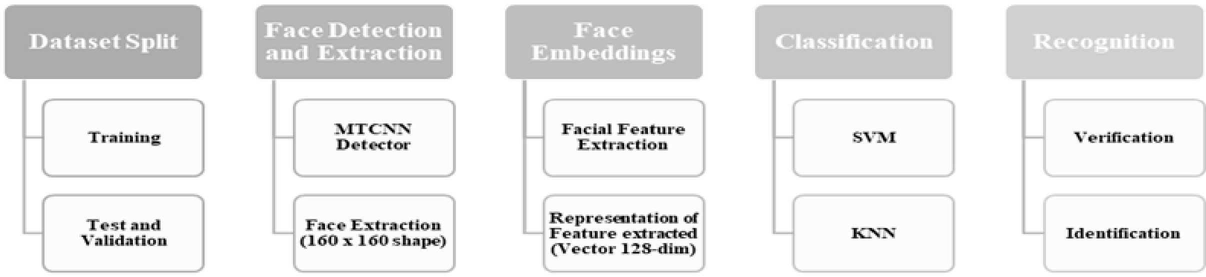


Figure 1. Overview of the proposed method.

DATABASE

RMFRD

The front-face images of media personalities and their corresponding masked face .There are 5,000 images of 525 people that wear masks in the dataset and 90,000 images of the same 525 people without masks. This actually the world's largest real-world masked face dataset, to the best of our knowledge (Zhongyuan Wang, 2020). Pairs of facial image samples are shown in Figure 2.

Figure 2. The pair on the left are no-masked faces, the pair on the right are masked faces.

Source: (Zhongyuan Wang, 2020)

SMFRD (LFW_ MIXED)

In the meantime, an alternate approach is used to increase the volume and diversity of the masked face recognition dataset and applied masks to existing public large-scale face datasets. A mask-wearing program base on the Dlib library that performs mask wearing automatically has been developed to improve data manipulation performance. This program is then used to apply masks to face images in common face recognition datasets, such as LFW at the moment (Gary B. Huang, 2009). A virtual masked face dataset of 500,000 face images of 10.000 subjects is also proposed. The virtual masked face datasets can be used in combination with their original unmasked counterparts in practice (Zhongyuan Wang, 2020). Pairs of facial image samples as shown in figure 3.

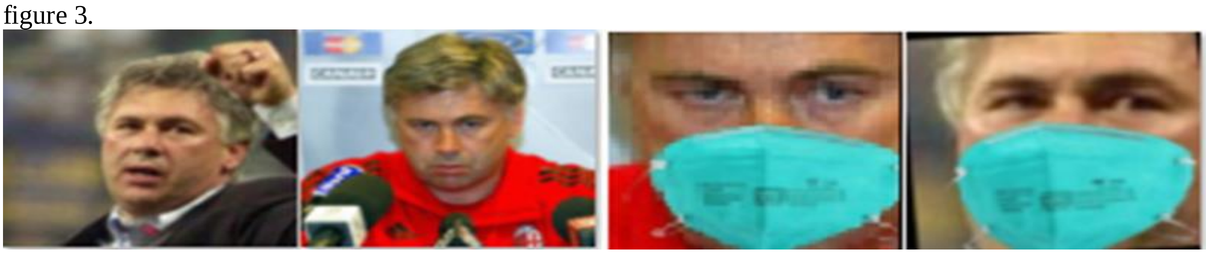


Figure 3. Figures on the left are non-masked faces, on the right are simulated masked faces.

Source: (Gary B. Huang, 2009)

SPLIT OF DATAET

In the proposed method, there are two types of datasets. The mixed and the normal dataset, the difference between them is the training datasets, for example for a dataset we need to split it into two parts (training and validation or test datasets), the only part which is mixed is only the training part, and this is the difference.

MIXED DATASET

The Testing (validation) dataset contains only masked faces. The mixed part is only the training datasets. Table 1. Illustrates the split of datasets

Table 1. The split of mixed datasets (LFW and RMFD).

LFW Mixed Dataset (90 people)	**RMFD Mixed Dataset (20 people)**
Train Dataset: 360 Masked+ Non-Masked Faces.	**Train Dataset: 249** Masked+ Non-Masked Faces.
Test (Validation) Dataset: 128 Masked Faces.	**Test (Validation) Dataset: 23** Masked Faces.

NORMAL DATASET

Normal datasets have not a mixed part in any part (validation or training), and Table 2. shows the split.

Table 2. Split of Normal datasets (RMFD and LFW).

LFW Dataset (90 people)	**RMFD Dataset (20 people)**
Train Dataset: 309 Non-Masked Faces.	**Train Dataset: 220** Non-Masked Faces.
Test (Validation) Dataset: 308 Masked Faces.	**Test (Validation) Dataset: 38** Masked Faces.

DETECTION AND FACE EXTRACTION

The proposed model for the detection and alignment uses unified cascaded CNNs and multi-task Learning, and to combine these two task, there are three phases to the proposed CNNs. It creates candidate windows easily in the first stage using a shallow CNN. Then, using a more complex CNN, it refines the windows to reject a large number of non-faces windows. Finally, it refines the result and outputs the locations of facial landmarks using a more efficient CNN (Hongchang Ku, 2020). The overview of stages is shown in Figure 4.

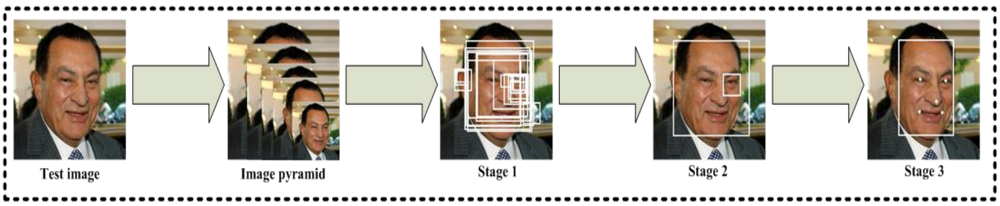


Figure 4. The overview of MTCNN stages.

The creation of the face detector class (MTCNN) is the first step to detect loaded images in order to get the list of bounding boxes, which define the height/width of, as well as lower-left corner. To prove the efficiency of

MTCNN, we detected the face landmarks even the topic does not talk about detection figure 5, and figure 6 illustrates that.

Figure 5. Illustration of masked face detection with face landmark estimation.

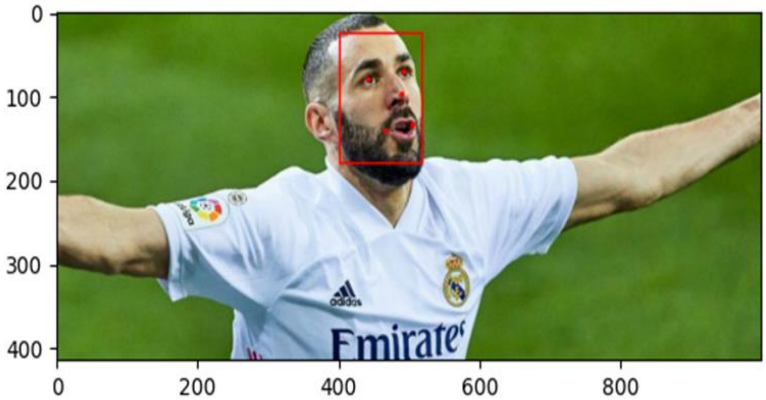


Figure 6. Illustration of rotated detection with face landmarks detection.

If we assume that our tests only have one face, we may determine the pixels of the boundary box. Sometimes a negative pixel index is returned by the library. This can be solved with the coordinates absolute value.
This little face image can be resized to the desired size via the PIL library; in particular, the shape desired for the FaceNet model is expected to be 160 to 160 input square facing.
When the function extract face() binds all this together, it loads a photo from the file name loaded and returns the extracted face. The image is taken with a single face, and the first detected face will be returned. An example is shown in Figure 7.

Figure 7. Illustration of a detected masked face with a shape of 160x160 (extracted face).

The reduction of the dataset is an important task. To do this, we have to reduce it by providing only detected faces with 160 to 160 shape (extracted faces) to compress them to Numpy array files (see Figure 8.).

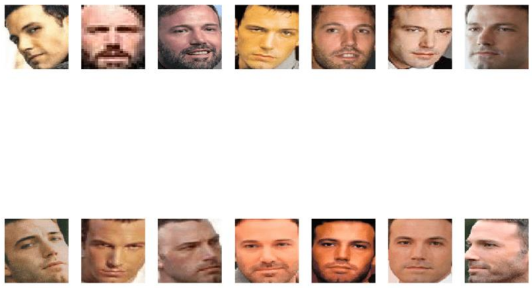


Figure 8. Example of reducing the dataset into detected faces only with 160x160 shape.

The images of training that contains only extracted faces are loaded, resulting in a sample of extracted faces (input) and a class label of the name as a string (output). The same process will be done by the validation dataset to be used as the testing dataset. Finally, both datasets are compressed to a Numpy array and saved.

CREATE FACE EMBEDDING

FaceNet is stacked linearly with 9 such inception modules Figure 9 shows its architecture. There are 22 deep layers (27, including the pooling layers). At the end of the last inception module, it uses global average pooling. The Fully connected layer will be utilized as the face descriptor. These descriptors become an embedding module for similarity descriptors. Max operator has been applied to features to develop a unique feature vector from a template. The network must be properly tuned to expect a significant boost for the particular task of face recognition and verification. To retrain the FaceNet model, we have to provide a number of images (masked and non-masked faces) (Christian Szegedy, 2015).

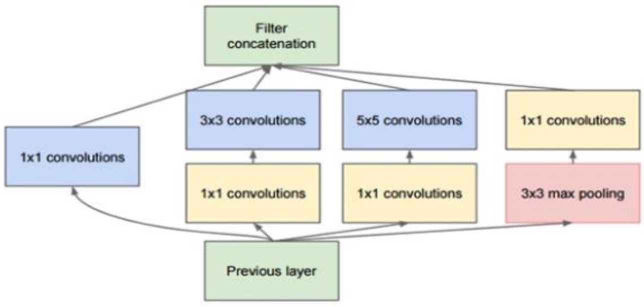


Figure 9. Illustration of the inception module used for FaceNet pre-trained model.

There are four branches in the module. The first branch takes a series of 1x1 local features from the input in order to learn them. The second branch applies 1 x 1 convolution to minimize the input dimensions until 1 x 1 convolution is performed. This greatly decreases the amount of calculation the network requires. The third branch is consistent with the second branch, but this time with 5x5 learning filters. The fourth branch carries out 3x3 max pooling with a Stride of 1x1. Finally, all four branches of the Inception-module converge where the channel dimensions are linked together before being added to the following network (Le, 2019).

Face embedding is the next task. The creation of face embedding is the representation of the facial feature to a vector. This vector can be compared with the other generated vectors. For example, one of the generated vectors, which is far from the tested vector, is considered the two people are different. When it is close, the result is the same person. The FaceNet pre-trained model that pre-processes the face, and creates the face embedding does the generation of face embedding. The embedding will be stored and will be used as an input for our classifier. To do that, we have to enumerate each face in both training and testing datasets to let the classifier making the prediction of embedding and names.
The prediction operates only if the pixels of the image are standardized (normalization). In Keras library, to extract the embedding vector and predict, we have to expand face array dimensions to let it be one sample (Chollet, 2018).

FaceNet has a batch layer and a deep CNN network. L2 normalization supports the deep CNN. The result of this normalization is then face embedding. The face embedding is performed Triplet loss during the training. The triple loss has a minimum distance between an anchor and positive when the identities identical (Gregory Koch, 2015). However, when identities are different, the distance value is higher between the negative and the anchor (see Figure 10.).

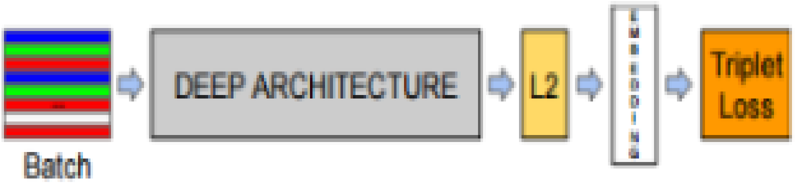


Figure 10. FaceNet Pipeline.

Source: (HARIRI, 2020)

CLASSIFICATION

Normalization of face embedding vectors is scaling the magnitude of vectors to 1 or unit length, using Scikit-Learn library has classes that normalize. The encoding of the file name string is the next step to make it an integer variable.
We choose two famous classifiers (SVM and KNN) after normalization of face embedding vector to achieve effective separation results. We have used the SVM and KNN model in the sci-kit-learn library and fit them later (Durgesh k Srivastava, 2009). To show the probabilities later, we have to set the classifier setting by making 'probability 'to 'True' (Gongde Guo, 2004).

EVALUATION

The Evaluation of the result can be done using evaluation metrics (Accuracy Score) which are based on name, and embedding prediction of both of classifier (SVM, KNN) and FaceNet pre-trained model).

The accuracy score function calculates either the fraction (default) or the number of the right predictions (normalize=false). The function returns the sub-set accuracy in the multi-label classification. If all expected labels for a sample correspond strictly to the true set of labels, the accuracy of the subset is 1.0; otherwise, it is 0.0 (scikit-learn, 2020).

RESULTS AND DISCUSSION

The Evaluation of our approach is based on evaluation metrics which are mentioned. Therefore, we have divided our method into scenarios based on the split of the dataset, which is mentioned in the method section.

The first scenario works with the LFW dataset at the beginning, the split of this dataset for 90 people is 309 image for training that contains only Non-masked faces and 308 image for validation or test datasets that contains only masked faces. The second scenario mix the LFW dataset. The split of this dataset for 90 people is 360 image for training that contains Non-masked faces mixed with a masked face, and 128 image for validation or test datasets that contains only masked faces. We propose in the third scenario to work with the RMFD dataset. The split of this dataset for 20 people is 220 image for training that contains only Non-masked faces and 38 image for validation or test datasets that contains only masked faces. Finally, the fourth scenario mix the RMFD dataset. The split of this dataset for 20 people is 249 image for training that contains Non-masked faces mixed with a masked face, and 23 image for validation or test datasets that contains only masked faces.
We follow the proposed approach on all the datasets, and we have evaluated the classification and prediction accuracy with SVM and KNN classifiers basing on the classification report.

Name prediction has two possible negative results. The negative results make the masked and Non-masked faces unknown, and the prediction is failed. The first one is when the tested image (masked or Non- masked face) is out of the datasets. And the second is when one of the scenarios has Low accuracies, which will make the accuracy of the prediction very low.

The Figure 11. Illustrates the results of all the scenario 1,2,3,4, and unknown face case.

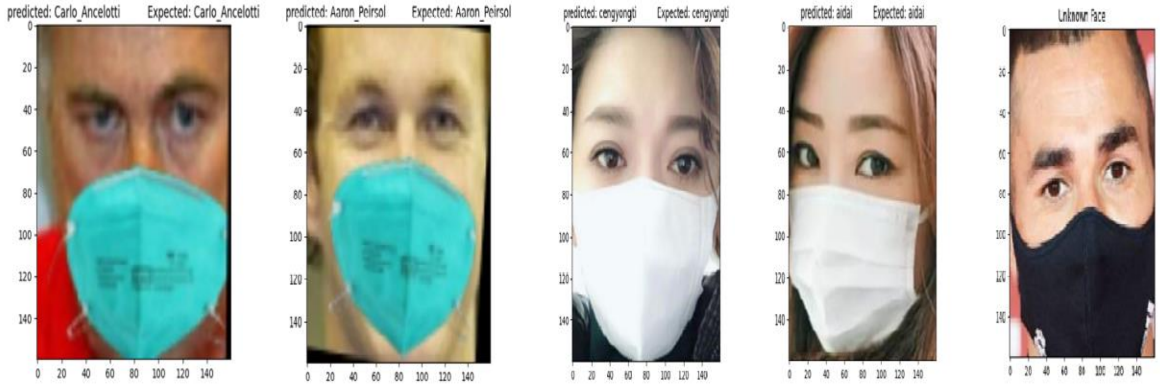


Figure 11. Illustration of the scenario 1,2,3,4 and unknown face case.

EVALUATION

Accuracy (%) of the proposed method for all the scenario has been measured on the datasets mention on the scenarios above as we discuss the scenario we have made a combination to get the solution at the end of this chapter. The tables of accuracy is illustrated below (Table 3, 4, 5, and 6).

Table 3. The accuracies and losses of scenario 1.

	Train Dataset	Test Dataset	Train Accuracy	Test Accuracy
Facenet + SVM	Non-Masked faces	Masked Faces	100	67.857
Facenet + KNN	Non-Masked Faces	Masked Faces	100	76.299

Table 4. The accuracies and losses of scenario 2.

	Train Dataset	Test Dataset	Train Accuracy	Test Accuracy
Facenet + SVM	Non-Masked faces + Masked	Masked Faces	97.778	91.406
Facenet + KNN	Non-Masked Faces + Masked	Masked Faces	100	81.25

Table 5. The accuracies and Losses of scenario 3.

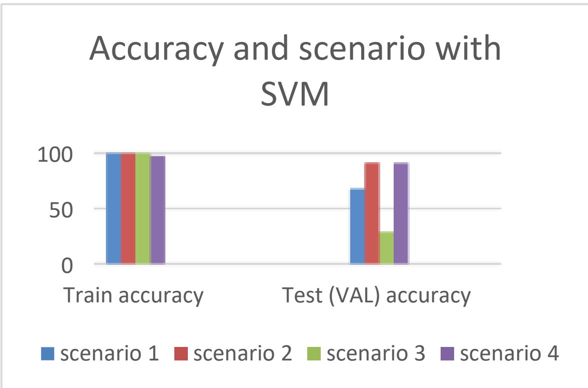
	Train Dataset	Test Dataset	Train Accuracy	Test Accuracy
Facenet + SVM	Non-Masked faces	Masked Faces	100	28.947
Facenet + KNN	Non-Masked Faces	Masked Faces	100	18.421

Table 6. The accuracies and Losses of scenario 4.

	Train Dataset	Test Dataset	Train Accuracy	Test Accuracy
Facenet + SVM	Non-Masked faces + Masked	Masked Faces	97.59	91.304
Facenet + KNN	Non-Masked Faces + Masked	Masked Faces	100	91.304

The tables show that the accuracies of mixed datasets are higher than the normal datasets, which means that when we mix the dataset in the training dataset with both Non-masked and masked faces, we will get better results.

Figure 12 illustrates the accuracies of the scenario. The first chart showed the accuracies when we used the SVM classifier and the second with the KNN classifier. There is not a large difference with SVM and KNN accuracies only on scenario 1, 2, and 3 on test (validation) dataset with the difference of 10% only. And
Still the same point to discuss in our proposed method is to mix with Non-masked and masked faces in train dataset to achieve the best accuracies in the validation (test dataset). As we see in scenario 1 and 3 the accuracies are very large in training 100% in scenario 1 and 3 for the both of the classifier SVM, and KNN. Very low accuracies on validation (Test) on the third scenario (18.421% using KNN, and 28.947% using SVM) and high but not the best in the first scenario (67.857% using SVM, and 76.299% using KNN classifier). The mixed dataset (scenarios 2 and 3) achieve an excellent result in training between 97% and 100 for both KNN and SVM classifiers. As we see, the lowest percentage in the validation (Test) is 81.25% in scenario 2 using KNN, and the other is around 90%, such that the best is 91.406 in scenario 2 using the SVM classifier.



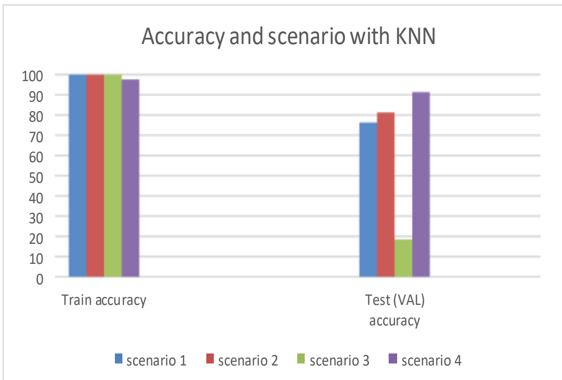


Figure 12. Accuracy of all scenarios with SVM and KNN classifier.

SELECTION OF THE BEST SCENARIO

To select the best scenario, we should choose one of scenarios 2, and 4 the best scenario. Therefore, we need to try the different parameter of SVM, and KNN classifier, to select finally the best scenario and define the best approach, the accuracies are shown in Table 7.

Parameters / Accuracy	**Linear**	**RBF**	**Sigmoid**
Train	97.778	100	93.976
Validation (Test)	91.406	**95.652**	60.870

Table 7. SVM parameters of scenario 4.

That is bring us to conclude the best result, which is the scenario 4, we used Radial Basis Filter as a kernel of SVM classifier, and we get 95.652% as a best result of the experiments. Finally, the split of Real World Masked Face Recognition to train dataset, which contains masked and unmasked faces, and Test (validation) dataset that contains only masked faces, using SVM classifier to predict names with RBF kernel. Therefore, the best Result is achieved.

CONCLUSION AND RECOMMENDATIONS

The pre-trained FaceNet model was employed in this work to improve masked face recognition. With two well-known datasets, we have evaluated this strategy. Our tested technique showed improved recognition rates on these datasets. FaceNet model trained on masked and non-masked photographs so provides improved precision for the recognition of a masked face. Although we focused on hat-induced masks, sunglasses, barley, long hair, mustache, and medical masks, we can still adapt our methods to a more complex set of other occlusive sources. Experiments are completed on masked face datasets, where the system is trained with both masked and unmasked faces. This strategy cannot, of course, satisfy all kinds of masks. To satisfy, it is necessary to mix masked and non-masked faces in the training dataset to let the model train with the specific type of occlusion.
It is important to develop and extend our work later in order to address various severe masks of face recognition. In parallel, Industry 4.0 and or Sustainable Technology are seeking to improve computer adoption and mechanisms with independent and smart data- and machine learning systems. Safety is vital while working with data. Our work may help these intelligent and self-governing industries become more self-governing, safe, precise, and effective, helping them to produce more and to waste less.

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