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REAL AND SIMULATED MASKED FACE RECOGNITION WITH A PRE-TRAINED MODEL

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ABSTRACT

Facial recognition has currently become indispensable owing to the efficacy of precise identification verification. Because of the distinctiveness of human biometrics, face recognition enables humans to communicate with technology while maintaining their privacy. Advancements in pre-trained models such as FaceNet have enabled improvement in identification accuracy in face recognition technology. Response to the Covid-19 pandemic has led to the replacement of conventional face recognition with masked face recognition. This change has encouraged the use of collaboration to resolve the related issues, which has resulted in the development of algorithms for face occlusion, collection of data on masked and unmasked faces and improvement of pre-trained models. Current research has utilised custom datasets or a specially produced dataset for masked face recognition. To increase the amount of data available for modelling, some studies have implemented mask simulation in facial photos. In this study, FaceNet is evaluated on two datasets: the real-masked face recognition dataset and the simulated masked face recognition dataset. Particularly, we highlight the performance of FaceNet on simulated masked faces. Using simulated masks achieved 67% accuracy, while the use of real masks achieved 84.3%. Results from the two datasets are compared with each other and with other studies using different pre-trained models with similar datasets. This study reveals that simulated masked faces perform less effectively than real masked faces, as corroborated by various other studies.

Keywords: *Masked face recognition, Face recognition, Pre-trained model, FaceNet.*

1. INTRODUCTION

In the area of deep learning and high-performance computing, the capacity of technology to accurately identify the identity of a person has gained great significance. In biometric identification, face recognition has produced better performance than retinal scans or fingerprint identification [1]. There are many types of identification that use human biometrics such as eyes, fingerprints and face for security verification. The advancement and usage of this technology has allowed humans to maintain their privacy owing to the uniqueness of human biometrics, which makes replicating a person's identity difficult. With advancements in verification technology, face recognition remains the most viable method of identity verification.

Considering the ongoing global Covid-19 outbreak, public health authorities have advised that individuals should wear face masks at all times to minimise infection rates. Consequently, contactless identity verification technology, specifically face recognition technology, has been recommended for security and attendance purposes. Masked face detection tasks have increased since the start of the Covid-19 outbreak. Extensive research has been conducted on face detection in general, aimed at addressing fundamental problems [2], [3], [4]. A study by Nieto-Rodríguez, Mucientes and Brea [5] developed a system that detects face masks in operating rooms and sounds an alarm when individuals are not wearing mandatory masks. The authors utilise a face classification system that detects the presence of face masks and categorises the faces into having or not having a surgical mask. This study is based on the use of the Viola–Jones face detector. The Viola–Jones face detector has been implemented in many machine-learning-based studies in tandem with convolutional neural networks (CNNs). Despite improvements in face recognition, there are still areas in which performance can be increased. The Face Attention Network is a face detector that employs face detection through the integration of a single-stage detector [6]. A deep learning model, InceptionV3, applies transfer learning to automate the process of identifying individuals with face masks [7]. The authors suggest that increasing the volume of data could further improve the results and facilitate the integration of face mask detection into a face recognition system. The field of face mask identification can be separated into 'traditional' machine learning approaches, 'deep learning'-based approaches and 'hybrid' approaches [1].

According to a recent study on face recognition accuracy [8], ‘pre-pandemic’ algorithms submitted to the Face Recognition Vendor Test (FRVT) 1:1 have yielded poorer performance in the recognition of face masks. The study included a discussion on variations of face mask types and how the algorithms used may not be suitable for recognising different mask types. To encourage improvement in the accuracy of masked face recognition, a masked face recognition competition was held during the 2021 International Joint Conference on Biometrics (IJCB 2021), which saw participation from various teams across the globe [9].

To address the lack of masked face images used for recognition, researchers often resort to the use of synthetic masked face datasets to train their models. In a study conducted by Damer et al. [10], they utilised a synthetic mask generation method based on a National Institute of Standards and Technology (NIST) report. NIST conducts the FRVT, which is intended to offer unbiased assessments of commercially available and prototype face recognition technology [11]. This report has been enhanced with recent algorithms and evaluated using one-to-one algorithms [8]. However, the report emphasises that it remains unclear whether the algorithms include an occlusion factor. Some studies on masked face recognition use the Dlib-ml toolkit [12] to augment masked face images from an existing or custom dataset.

The ongoing research on masked face recognition has prompted questions regarding the effectiveness of pre-trained models on simulated mask datasets. Anwarul and Dahiya [13] have discussed the various factors that can affect face recognition performance, including intrinsic components such as age, facial expressions and biological features, as well as extrinsic factors such as face occlusion, environment illumination and pose variation. While these factors are relevant for real-masked faces, they are not necessarily applicable to simulated masked faces, which are merely simulations. Research on masked face recognition with pre-trained models is ongoing, from the implementation of the support vector machine (SVM) algorithm to the use of cropped-based methods to increase the utility of masked face datasets. We hypothesise that despite the fact that simulated masked faces cannot be described by the same features as real-masked faces, methods that emphasise increasing model performance can increase the viability of using simulated masked faces in face recognition.

To explore this topic, we propose a study that compares the accuracy of masked face recognition using FaceNet, a deep learning model that directly learns the mapping of a face image. Specifically, we compare the performance of FaceNet on two datasets: the Real-World Masked Face Recognition Dataset (RMFRD) and the Simulated Masked Face Recognition Dataset (SMFRD), both of which were created to facilitate the development of effective face recognition algorithms for masked faces [14]. By comparing the performance of FaceNet on these two datasets, we hope to gain insights into the effectiveness of this particular pre-trained model on simulated masked faces and reveal the overall performance of simulated masks in masked face recognition. This study uses performance metrics to compare the results from both real mask and simulated mask datasets. We focus mainly on the accuracy metric for comparison between the datasets in this study uses and comparison with other studies on masked face recognition.

2. LITERATURE REVIEW

Face recognition technology has undergone several advancements that have increased face recognition accuracy. This technology with its

Author(s)	Methods	Key findings	Ref
Vu et al. (2022)	Combination of deep learning and Local Binary Pattern (LBP) with MobileNet (RetinaFace), a deep learning facial detector.	Performance from the proposed method outperforms Dlib and InsightFace, with 87% F1-score on COMASK20 dataset and 98% F1-score on Essex dataset.	[18]
Anwar & Raychowdhury (2020)	FaceNet and MaskTheFace, a tool to mask faces, with VGGFace2 dataset	Utilising a tool to increase current dataset by generating masked face have effectively increase the accuracy for masked recognition by ~38%.	[19]
Hariri (2021)	Pre-trained deep Convolutional Neural Networks (CNN) as feature extraction; VGG-16, AlexNet and ResNet-50, with Bag-of-features paradigm as feature maps and Multilayer Perceptron as classification.	The high performance through the proposed method compared to transfer learning method indicates that fully connected layers of pre-trained models are leaning towards dataset-specific features.	[20]
Ullah et al. (2022)	DeepMasknet framework, with mask detection and masked face recognition (MDFR) dataset.	The accuracy of face mask detection is 100% and 93.33% for masked face recognition when using the proposed framework, that functions as both face mask detection and masked face recognition.	[1]
Nawal Younis Abdullah & Ahmed Mamoon Fadhil Alkababji (2022)	Combination of two CNN models built from scratch, with Haar feature-based cascade classifiers as face detector.	The performance of the combined models achieves an accuracy to 95% compared to other methods, improved generally when using Adam optimiser	[21]

recent upgrades can be commonly found in handheld devices and laptops. Face recognition technology would not have been able to advance far without the use of pre-trained models such as ResNet [15], VGGNet [16], FaceNet [17] and others. From the basis of the pre-trained model, various research has been conducted which uses a conventional pre-trained model with other models or uses a custom algorithm alongside a pre-trained model. Face recognition has achieved high performance when faces are not occluded. However, in the case of occluded faces, face recognition performs very poorly. This is because certain facial features are

Table 1:Summary of studies regarding masked face recognition

covered and are not visible, making it more challenging for technology to accurately identify a person. Table 1 summarises the studies on masked face recognition.

Mandal, Okeukwu and Theis [22] presented a ResNet-50-based method for identifying individuals with masked faces. Transfer learning was used to adapt the pre-trained ResNet-50 model to the RMFRD, and architectural hyperparameters were modified according to the dataset. The objective of developing RMFRD was to enhance the efficiency with which existing face recognition systems recognised faces. The authors selected 77 classes of both masked and unmasked faces to compare their results. According to their experiment, the accuracy rate for unmasked faces was 87.7016% and 47.91% for masked faces. In a proposed approach for face detection and classification using deep learning, a CNN was combined with Haar cascade to detect faces, with the CNN serving as the classification model [23]. The proposed CNN achieved an accuracy ranging from 97.55% to 98.43%, while maintaining less computational complexity and a reduced number of layers compared to other models.

Numerous studies have explored various methods for achieving high accuracy in masked face recognition (MDFR). A study used a cropping-based approach with the Convolutional Block Attention Module (CBAM) to extract refined features [4]. The CBAM contains both channel attention and special attention modules, allowing for the exploration of optimal cropping. In another study, a Single-Shot Multi-Box Detector was used in masked face detection with FaceNet as the pre-trained model, resulting in 98% accuracy [24]. Moreover, some studies have focused on improving deep learning architectures by combining different methods. For instance, the ResNet50 model was improved by implementing the ArcFace loss function to train the model, resulting in increased accuracy. Khan et al. [25] discussed various methods for improving face

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recognition accuracy, including Fisherfaces, EigenFaces and Local Binary Pattern (LBP) Histogram. The authors employed transfer learning on AlexNet, a pre-trained network, to enhance their approach, achieving 97.95% accuracy.

An extensive MDFR study on both real and simulated masked faces was conducted [10]. The authors used a custom model for their research, in which participants were instructed to acquire data on three different days under varying conditions. The authors compared a synthetically masked dataset as both the reference and test. The performance of verifying both the training and testing synthetic masked face images was marginally better than comparing a non-masked face and synthetic masked face. The results of the face recognition test using ArcFace were obtained by verifying a reference synthetic masked face and performing a probe (test) with a real-masked face (BLR-M12P) and a probe with a simulated masked face (BLR-SMP). For BLR-M12P, the verification yielded an area under the curve (AUC) value of 0.98 in the receiver operating characteristics (ROC) curve. The verification performance for BLR-SMP was 0.99 for the AUC-ROC.

2.1 Pre-trained Model

The use of pre-trained models in face recognition obviates the need to train the model from scratch, reusing previous knowledge learned from other tasks and applying it to new tasks. Studies and results conducted with different pre-trained models are presented in Table 2. From the table shown, most studies have used RMFRD as a dataset, whereas FaceNet has been used with different masked face datasets [28]. Neither have been applied with SMFRD, except AlexNet [26]. In terms of accuracy, FaceNet has achieved the highest accuracy for occluded faces with the datasets we used in this study. The performance may vary when using different datasets as opposed to SMFRD. Naser et al. [28] employed a method comprising the Multi-Task Cascaded CNNs (MTCNN) and linear support vector classifier, with FaceNet as the model, to achieve an accuracy of 99.50%. The authors used a dataset of simulated masks to train the FaceNet model for MDFR. However, we require FaceNet to be trained on RMFRD and SMFRD for consistency.

AlexNet achieves the highest accuracy for RMFRD, while simultaneously achieving 90% accuracy for SMFRD. AlexNet has been combined with SVM and MTCNN to achieve the intended results [26].

Figure 1: FaceNet architecture

2.2 FaceNet

FaceNet is a deep learning model that utilises a batch containing an input layer and a deep CNN layer for face embedding, followed by L2 normalisation. This method allows the model to use a small sample of face images to train an initial model. The initial model can be implemented without retraining when new models are provided, as FaceNet uses Euclidean space to train according to the distance between facial models consisting of similarities between one another. The architecture of the FaceNet model is depicted in Figure 1. A triplet loss is employed in this architecture, which minimises the distance between an input (anchor) and a positive state, in which both identities are similar, and maximises the distance between the anchor and a negative state, in which different identities are present.

A study on face recognition using FaceNet was conducted by William et al. [29]. The authors used public datasets to obtain the accuracy of this face recognition method. The model is trained by using pre-trained data from existing models, CASIA-WebFace and VGGFace2. Next, FaceNet is compared with other face recognition methods. Results show that the FaceNet method achieves approximately 100% accuracy from the different sets of tests. The authors also note that the accuracy of FaceNet is heavily influenced by the pre-trained model in use. Overall, FaceNet performs marginally better compared to other face recognition methods that were previously proposed, owing to the triplet loss.

The model performs admirably with respect to JPEG compression, down to a JPEG quality of 20. Even with the use of low-quality face images, the performance drop is minor and acceptable. Moreover, this model only requires minimal alignment, within the vicinity of the face area. The face recognition pipeline, as depicted in Figure 2, comprises four stages: face detection, face alignment, face encoding and face classification. The face detection stage employs the MTCNN algorithm, which is based on research from He et al. [15] on joint face detection. The face alignment stage aligns the faces with the eye lines, and the face encoding stage uses FaceNet to extract the

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vectors of the person's face. Finally, the face classification stage involves classifying images based on Euclidean distances, as per the FaceNet architecture, where the Euclidean distance directly corresponds to face similarity. Hence, owing to the limited amount of data available, this pre-trained model is used in our study.

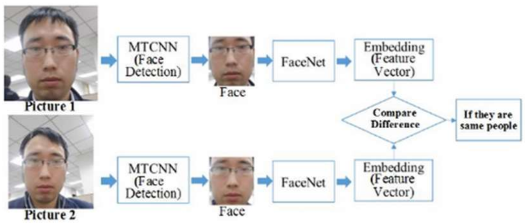

Figure 2: Face recognition stages

Our research uses RMFRD and SMFRD as our main datasets to train the FaceNet model. In the review, we discuss the different performances of pre-trained models when using real-masked face datasets and, to an extent, simulated masked face datasets. However, despite one of the studies discussed involving the use of FaceNet, the authors do not employ the same datasets. Hence, with the lack of masked face data available, we employ simulated masks of varying designs to be combined with real faces. This increases the data size and likely increases the accuracy of MDFR. However, regarding the use of a simulated masked face dataset, Damer et al. [10] discussed the effectiveness of using simulated masks to reflect real mask scenarios when evaluating face recognition performance. The authors argued that simulated masks do not reflect real-masked faces, as they exhibit variations in mask shape, colour and texture. This may be seen as an optional issue. The main difficulty in using simulated masked faces for face recognition is the inability for the simulated mask to reflect the environmental factors. To our understanding, the use of simulated masks on real face images may not have the profound effect needed in increasing the accuracy performance of MDFR. We address this problem by applying RMFRD and SMFRD to FaceNet, alongside previous research [26] for analysis.

3. RESEARCH METHODS

The proposed research involves two phases: the collection and preparation of the data and the use of FaceNet as a pre-trained model for MDFR on both real and simulated mask datasets. A conventional face recognition algorithm is utilised by employing the FaceNet architecture, a pre-trained deep learning model. FaceNet is selected based on its performance on face recognition tasks, as stated previously, when compared with CASIA-WebFace and VGGFace2. The parameters are fine-tuned based on the datasets used, with the aim of accurately identifying individuals from both datasets and comparing the results. With this method, we can determine the effectiveness of a simulated masked face model to identify individuals.

Table 2: Evaluation of Studies on Pre-Trained Model

Model Used	Dataset	Results	Ref
ResNet50	Real Masked Face Recognition Dataset (RMFRD)	• Accuracy: 47.91%	Mandal, Okeukwu and Theis [22]
AlexNet	• Real Masked Face Recognition Dataset (RMFRD) • Simulated Masked Face Recognition Dataset (SMFRD)	• Accuracy: 88.89% • Accuracy: 85.21%	Marwa and Kais [26]
VGG-16	Real Masked Face Recognition Dataset (RMFRD)	• Accuracy: 68.17%	Chandra and Reddy [27]
FaceNet	• CelebA • MFR2 • WiderFace • LFW • MegaFace Challenge	• Accuracy: 99.50%	Naser et al. [28]

Facial occlusion reduces the number of features that are considered. We apply the approach of simply cropping out the occluded part from the faces. However, the results obtained are uneven, as some individuals wear accessories, such as glasses and hats. An alternative option is to remove these images; however, owing to the

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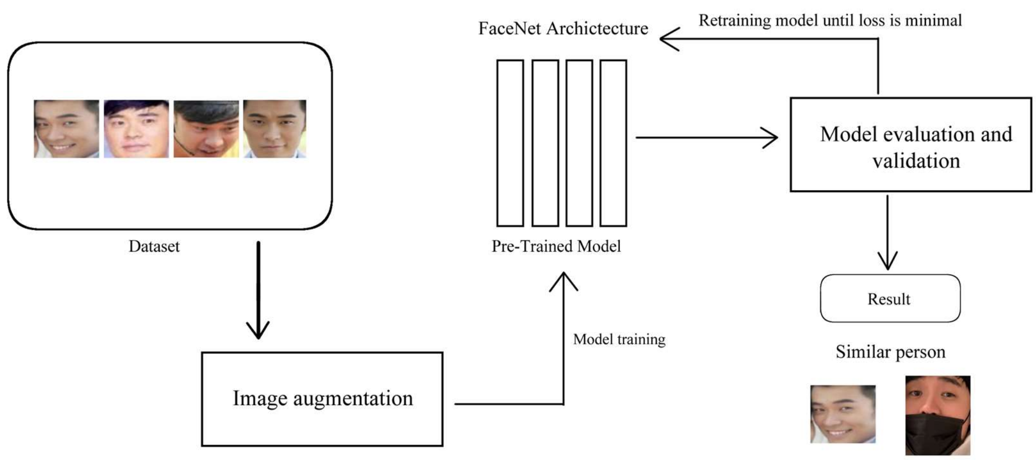

Figure 4: Schematic representation of masked face recognition

scarcity of data, we drop this option.

We increase the size and diversity of the data through image augmentation techniques applied on the training images, such as rotation, zooming and flipping. To detect initial facial features, MTCNN is utilised, which involves generating a border around the facial structure and eyes. The existence of occlusion on faces presents challenges in face recognition. The data are then trained with the FaceNet model to perform MDFR, after face detection is conducted. Validation is carried out using a set of validation images. The results of training on both real and simulated masked face datasets are compared and tabulated. The flowchart of the MDFR process is shown in Figure 3, while the methodology is depicted schematically in Figure 4.

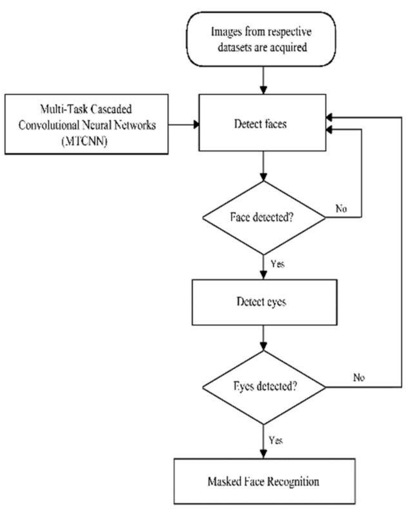

Figure 3: Flowchart of Masked Face

3.1 Datasets

The datasets used for this study are RMFRD and SMFRD [14]. These datasets are constructed to improve existing face recognition, specifically in MDFR. The RMFRD dataset comprises 5000 masked faces of 525 individuals and 90,000 normal faces, while the SMFRD dataset contains 500,000 simulated masked faces of 10,000 subjects. SMFRD is a dataset in which simulated masks are applied to an already existing large-scale public face dataset. Figure 5 shows a few examples of images from RMFRD whereas figure 6 shows few examples of images from SMFRD.

Figure 7: Augmented images from RMFRD and SMFRD

Figure 6: Images of simulated masked faces from SMFRD

3.2 Data Preparation and Pre-Processing

Figure 5: Images of real masked faces from RMFRD

Figure 5: Images of unmasked and masked faces from

We selected only 10 individuals from RMFRD, totalling 151 images for masked face predictions, using the same classes for unmasked face predictions. These 10 individuals were chosen based on having at least 8 images each for both masked and unmasked faces to ensure a reliable test outcome. A 70%-30% train-test split was applied, and we applied random horizontal flips to the training images. As for SMFRD, only 670 people were chosen, comprising a total of 1345 images and of the 670, 30 people were used for testing owing to a lack of available images for each person, unlike the case for RMFRD. Consequently, the image data were divided into training and testing sets to address this issue. Furthermore, both datasets were iteratively augmented randomly in each batch to increase its size and diversity. After horizontal flipping, there were approximately 300 images in RMFRD, whereas SMFRD had 2690 images after the augmentation of images. Figure 7 shows an example of augmentation of an image from RMFRD and SMFRD.

3.3 Performance Metrics

The outcomes of the experiment are derived from training the pre-existing FaceNet model with the available datasets. The results from both RMFRD and SMFRD are tabulated in terms of the four performance metrics, i.e. accuracy, precision, recall and F1-score. The accuracy, precision, recall and F1-score from the face recognition experiment are calculated from Equations (1), (2), (3) and (4).

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

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

(2)

$$Recall = \frac{TP}{(TP+\quad)} \quad (3)$$

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

Table 3: Performance Metrics

Masked Face Images	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
RMFRD	84.3	86.0	77.0	81.0
SMFRD	67.0	67.0	67.0	67.0

FP = False Positive, *TP* = True Positive, *FN* = False Negative, *TN* = True Negative

4. RESULTS AND DISCUSSIONS

4.1 Performance Comparison Between RMFRD and SMFRD

In this study, we utilised RMFRD, selecting 310 images of real-masked faces from 10 selected subjects. We specifically chose subjects of which at least 8 images were available to ensure effective model training and increase the amount of available data for training. For SMFRD, we selected 1345 masked faces of 670 individuals for training and 52 masked faces of 30 individuals for validation.

In the first testing phase, FaceNet was trained and validated on data sourced from RMFRD to evaluate the performance metrics. In the second testing phase, FaceNet was trained and validated on data from SMFRD, which consisted of simulated masked faces. The results of these tests are presented in Table 3. Our analysis shows that the accuracy for masked faces is higher in RMFRD (84.3%) than in SMFRD (67.0%). Precision measures the fraction of detected faces that are similar to the validation data, while recall indicates the ability to properly identify positive cases. The F1-score is a measure of the test's accuracy based on the mean of the precision and recall metrics. As seen in the table, RMFRD provides higher precision, recall and F1-score than SMFRD.

Our assumptions regarding the factors that may affect the performance of the SMFRD are related to facial alignment and the absence of environmental factors that impact real-masked faces. Unlike real face masks, simulated masks are often placed on the lower region of the face without consideration of the facial poses of the person, which may affect the accuracy of the recognition system. Additionally, environmental factors such as illumination and various poses, which are present in real-life situations, do not apply to simulated images. Although variations in simulated mask type, shape, and colour can be explored to address this issue, it is difficult to replicate the full range of interactions between real masks and the environment.

4.2 Study Limitations and Suggestions

The dataset used in this study was limited owing to system constraints that hindered the efficient execution of testing. Furthermore, the size of the SMFRD was relatively small for each person, as public datasets have been mainly used for small-scale tests. Anwar and Raychowdhury [19] found that accuracy improves with an increase in the amount of data, which suggests to us that increasing the number of simulated masked face images with more variations may improve the performance of the system. Therefore, we recommend using a larger number of simulated face mask images with greater variation in environmental factors to enhance the accuracy of the recognition system.

4.3 Results Analysis

Based on the results obtained, SMFRD achieves a lower accuracy than RMFRD when using FaceNet as the pre-trained model. In regard to the lack of MDFR when using FaceNet as the pre-trained model, this study has provided useful results. The results show that using real masked faces to train a model is better than training with simulated masked faces dataset. We can state that the factors that affects real situations are viable in ensuring the peak model performance. However, the use of AlexNet as the pre-trained model and employing the same datasets yielded an accuracy result of 88.89% for RMFRD and 90.0% for SMFRD [26]. This highlights a contradiction regarding the effectiveness of using simulated masks to train a face recognition model, whereby their results show higher accuracy with the use of the simulated face mask dataset while our results show the real face mask dataset with the higher accuracy. However, we do use a smaller dataset as compared to [26], which may cause the accuracy results for FaceNet to be lower than those for AlexNet.

5. CONCLUSION

In our study, we use FaceNet as a pre-trained model with a face recognition algorithm and compare the performance of training a model with two datasets: RMFRD and SMFRD. The performance of the trained model was evaluated using accuracy, precision, recall and F1-score metrics, which are presented in tables for both datasets. Results show that RMFRD realises an accuracy of 84.3% compared to the SMFRD accuracy of 67%. The environmental factors that affect real-masked faces are not viable to the use of simulated masked faces. From this study, it is concluded that training a model with simulated masked face dataset has lower performance compared to real masked face dataset.

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