A Novel Hybrid Approach to Masked Face Recognition Using Robust PCA and GOA Optimizer

Mohammed Eman[1*], Tarek M. Mahmoud[2,3] and Tarek Abd-El-Hafeez[3,4]

[1] Computer Science Department, Faculty of Computing and Artificial Intelligence, Beni Suef University, Egypt
[2] Computer Science Department, Faculty of Science, Minia University, EL-Minia, Egypt
[3] Faculty of Computers and Artificial Intelligence, University of Sadat City, Egypt
[4] Computer Science Unit, Deraya University, EL-Minia, Egypt

Abstract

The use of face masks has become ubiquitous across a wide range of industries and professions, including healthcare, food service, construction, manufacturing, retail, hospitality, transportation, education, and public safety. To overcome this challenge, masked face recognition has emerged as a vital technology in recent years. By utilizing advanced algorithms and deep learning techniques, masked face recognition enables accurate identification and authentication of individuals even in scenarios where masks are worn. This paper presents a novel method for recognizing faces with masks. The proposed method integrates deep learning-based mask detection, landmark and oval face detection, and robust principal component analysis (RPCA) to accurately identify and authenticate individuals wearing masks. A pretrained ssd-MobileNetV2 model is utilized to detect the presence and location of masks on a face, while landmark and oval face detection are used to identify and extract important facial features. RPCA is applied to separate the occluded and non-occluded components of an image, making the method more reliable in identifying faces with masks. To further optimize the performance of the proposed method, the Gazelle Optimization Algorithm (GOA) is used to optimize both the KNN features and the number of k for KNN. Experimental results demonstrate that the proposed method outperforms existing methods in terms of accuracy and robustness to occlusion, achieving a recognition rate of 97%. This represents a significant improvement over existing methods for masked face recognition. The proposed method has the potential to be applied in a wide range of real-world scenarios, such as security systems, access control, and public health measures. The results of this study demonstrate that the integration of deep learning-based mask detection, landmark and oval face detection, and RPCA can improve the accuracy and reliability of masked face recognition, even in challenging and complex environments. The proposed method can be further improved and extended in future research to address other challenges in this field.

Keywords: Face masks problem; robust principal component analysis; gazelle optimization algorithm; KNN; GOA.

Introduction

Face masks are widely used in various settings and industries to protect workers and the public from the spread of infectious diseases. Some jobs that commonly require the use of face masks include healthcare workers, food service workers, construction workers, manufacturing workers, retail workers, hospitality workers, transportation workers, education workers, and public safety workers. However, face detection systems are facing significant challenges when it comes to detecting faces that are partially or fully covered by face masks. Some of the key challenges include reduced accuracy, false positives and negatives, the need for retraining, dependence on other features, privacy concerns, limitations in low-light conditions, adaptation to different mask types, and impact on system performance.

To accurately detect masked faces, face detection systems may need to be retrained using data that includes masked faces, which can be time-consuming and resource intensive. Additionally, the use of face detection systems in public spaces can raise privacy concerns, particularly when individuals are wearing masks and cannot be accurately identified. As different types of masks can present different challenges for face detection systems, adaptation to different mask types may also be necessary.

The Covid19 pandemic has changed the way people interact with each other. Governments have implemented measures such as wearing masks, social distancing, and staying at home to reduce the spread of the virus. While wearing masks helps protect people from the virus, it poses a challenge for facial recognition systems to accurately identify individuals.

Traditional passwords and security measures are not always sufficient to keep important information secure, leading researchers to focus on biometric technology, which is difficult to imitate and effective at keeping things safe (Jain et al., 1996). As a result, facial biometrics have gained attention as a reliable means of recognizing individuals. Biometric facial recognition technology is widely used in applications such as security systems, access control, and law enforcement. However, with the widespread use of masks due to the COVID-19 pandemic, facial recognition systems face significant challenges in identifying masked faces. This has created a need for new methods that can accurately identify individuals wearing masks. The goal of masked face recognition (MFR) is to match a masked face with unmasked or masked faces. Due to the COVID-19 pandemic, developing new methods and algorithms for detecting and recognizing people wearing or not wearing masks has become an important area of innovation to reduce and prevent the spread of COVID-19.

Motivation

The COVID-19 pandemic has had a profound impact on the way people interact with one another, forcing governments around the world to implement measures like wearing masks, social distancing, and staying at home to mitigate its spread. Face masks have become a critical tool in various settings and industries to protect both workers and the public from infectious diseases. Healthcare workers, food service workers, construction workers, manufacturing workers, retail workers, hospitality workers, transportation workers, educational workers, and public safety workers are among the many professionals who commonly wear face masks on the job. While face masks are essential in preventing the spread of COVID-19, they also pose a significant challenge for facial recognition systems. These systems rely on visual identification, which is made difficult when part or all of an individual's face is obscured by a mask. As traditional passwords and security measures can be vulnerable to hacking and other forms of security breaches, researchers have turned to biometric technology as a more reliable and secure means of authentication. Biometric technology is difficult to replicate and is effective in keeping sensitive information safe.

Facial biometrics have gained attention as a reliable means of recognizing individuals and are widely used in various applications, including security systems, access control, and law enforcement. However, the widespread use of masks due to the COVID-19 pandemic has created a significant challenge for facial recognition systems. These systems need to be able to accurately identify individuals who are

wearing masks, which is especially important in high-security settings such as airports, government buildings, and financial institutions. To address this challenge, researchers are exploring new methods that can accurately identify individuals wearing masks. One approach involves using thermal imaging cameras to detect the heat signature of an individual's face, which can be used to verify their identity. Other methods include using voice recognition or other biometric identifiers, such as fingerprints or iris scans, to supplement facial recognition systems.

As the COVID-19 pandemic continues to impact daily life, the need for reliable and accurate identification methods will only grow. Researchers and developers must continue to innovate and adapt to ensure that facial recognition systems remain effective even in the face of new challenges such as the widespread use of masks.

Contribution

Detecting faces that are partially or fully covered by masks is a challenge that face detection systems face, especially in the context of the COVID-19 pandemic. The widespread use of masks has made it difficult for these systems to accurately identify individuals, which can have significant implications for security and surveillance applications. Several factors contribute to the challenge of detecting masked faces, including reduced accuracy, false positives and negatives, the need for retraining, dependence on other features, privacy concerns, limitations in low-light conditions, adaptation to different mask types, and impact on system performance.

To address these challenges, an integrated approach can be used, which combines several techniques to improve the accuracy and performance of face detection systems when dealing with masked faces. For instance, one approach involves using two pretrained deep learning-based algorithms, one for mask detection and one for landmark and oval face detection. This approach can help detect faces that are partially or fully covered by masks, while also identifying the shape and position of the face.

Another technique that can be used is Robust Principal Component Analysis (RPCA), which can help identify faces with masks by separating the mask from the face using low-rank and sparse decomposition. This approach can help improve the accuracy and robustness of face detection systems when dealing with occluded faces.

The K-Nearest Neighbors (KNN) classifier can also be used for face recognition, where a large dataset of images is used to train the classifier to recognize faces. This approach can help identify individuals even when their faces are partially or fully covered by masks, improving the accuracy of face detection systems.

Finally, The Gazelle Optimization Algorithm (GOA) can be used to select the features used for training the KNN classifier and optimize the k number. This approach can help reduce the computational cost of training the classifier and improve its accuracy. The integration of multiple techniques such as deep learning-based algorithms, RPCA, KNN classifier, and GOA algorithm can help improve the accuracy and performance of face detection systems when dealing with masked faces. As the use of masks continues to be prevalent, it is essential to invest in research and development of such techniques to ensure the accuracy and effectiveness of face detection systems in various settings and applications.

Paper organization

The paper is organized as follows: In Section 2, the literature of existing studies is presented; Section 3 introduces our proposed hybrid method in detail. Section 4 presents the experimental results and discussion. Section 5 concludes this paper. Finally, Section 6 points out the future research ideas.

Related Work

In this section, we will discuss the existing research on recognizing faces that are partially or fully covered by masks. Previous approaches can be divided into two categories: traditional machine learning techniques and deep learning techniques.

In the years following the pandemic, many researchers have focused their efforts on finding a solution to the issue of confusion caused by masks. Some researchers have proposed methods based on machine learning

techniques, such as KNN for face recognition (Sasirekha and Thangavel, 2019). However, these methods are sensitive and can be affected by the occlusion caused by masks. On the other hand,(Zhao et al., 2022) some researchers have proposed a Consistent Sub-Decision Network (CSDN) that specifically targets low-quality images of masked faces. In one study, the authors proposed a CSDN that achieves more consistent model inferences by focusing more on the upper part of the face without occlusion and extracting more discriminative features.

Recently, many researchers have proposed methods that combine deep learning-based mask detection with face recognition. Convolutional Neural Network (CNN) models have been used to develop several face detection approaches specifically designed for identifying faces with masks. These approaches use the accurate results of deep learning algorithms to address the problem of recognizing faces that are partially or fully covered by masks. (Adhikarla and Davison, 2021; Vu et al., 2022)

Aswal and Tupe et al. (Aswal et al., 2020) proposed a method for detecting and identifying faces with masks using a single camera. Their approach is based on two methods: one that uses a single-step pretrained YOLO-face/trained YOLOv3 model on a set of known individuals, and another that uses a two-step method based on a pre-trained one-stage feature pyramid detector network called RetinaFace.

The authors suggested and verified a technique to distinguish between masked, unmasked, and incorrectly masked individuals using a mobile application called MadFaRe (Kocacinar et al., 2022). The framework of Adhikarla and Davison (Adhikarla and Davison, 2021) consists of eight object detection models and four face detection models. Many models are being used to improve face mask identification, with categories such as "with-mask," "without-mask," and "unsure." While the results show an improvement in accuracy, there are still costs associated with time complexity and computation.

In (Qi and Yang, 2020), a novel facial recognition technique for partially occluded faces was presented, which uses a Multi-Task Cascaded Neural Network (MTCNN) for face detection and extracts LBP features from the non-occluded area. Ding et al. (Ding et al.,

2020) proposed a two-branch convolutional neural network (CNN) architecture that aims to improve the performance of masked face systems. The global branch of the CNN generates top convolutional feature maps using the ResNet-50 model, while the local branch focuses on localizing the most discriminative latent area in masked facial images using a latent part detection approach. By integrating CNN parameters in both branches, the proposed architecture can retrieve more useful features while keeping the branches smaller. This integration allows the model to achieve better performance in identifying masked faces. The authors suggest that this approach can improve the accuracy and robustness of masked face systems, which are increasingly important in the context of the COVID-19 pandemic.

Singh et al. (Singh et al., 2021) used two pre-trained CNN models, YOLOv3 and Faster R-CNN, to address and improve the results of this challenge. These integrated models improve the performance and accuracy of masked face detection, although complex problems remain. Similarly, Zhu et al. (Zhu et al., 2021) used two CNN models. The first level uses the Dilation RetinaNet Face Location (DRFL) network to locate faces in crowds, while the second level uses the SRNet20 network to classify faces wearing masks.

Many research papers have introduced the use of transfer learning mechanisms with various deep learning models. One approach uses an InceptionV3 pre-trained model to implement transfer learning, and the Simulated Masked Face Dataset (SMFD) is used (Jignesh Chowdary et al., 2020). Another system uses transfer learning and consists of three different models for the detection phase, including Support Vector Machine (SVM), Decision Trees, and an Ensemble Algorithm embedded with ResNet50. The ResNet50 deep learning model is used for the feature extraction phase. The system is tested using the RMFD, SMFD, and LFW datasets (Loey et al., 2021).

Suresh et al. (Suresh et al., 2021) developed a system using MobileNet that is capable of recognizing individuals who are not wearing masks and transmitting their image to authorized staff members. In a separate study by Lodh et al. (Lodh et al., 2020), a model was created by fine-tuning MobileNetv2 on a collection of masked and unmasked images in the proposed system. The system achieved an accuracy of over 98%. This approach identifies

individuals who are not covering their faces before recognizing their faces.

In another study, the Multi-Task Cascaded Neural Network (MTCNN) (Rusli et al., 2021) was used to detect faces in photos of individuals wearing masks, and the system was trained using the LeNet algorithm to compare the accuracy of masked and unmasked classifications. Deep learning methods show promise for recognizing faces with masks. However, there is a need for large-scale datasets of masked faces for training, and such datasets are not easily accessible or sufficient.

Saleh et al. (Saleh et al., 2021) proposed a two-stage approach. In the first stage, texture and color moment features are extracted from facial photos using 3705 images by combining these features. In the second stage, the face images are classified using a Multi-Layer Perceptron (MLP) and the extracted features. Wu (Wu, 2021) developed a system based on subsampling and introduced a novel method for the recognition process. An attention machine neural network and a ResNet were used to implement the technique. The Real World Masked Face Recognition Dataset (RMFRD) and Synthetic Masked Face Recognition Dataset (SMFRD) databases were used in the studies, and the results show strong performance due to the low time cost and high accuracy rate.

Oumina et al. (Oumina et al., 2020) proposed a method that combines classical machine learning with deep learning. They classify the extracted features using classifiers such as SVM and KNN, in conjunction with pre-trained deep learning models like VGG19, Xception, and MobileNetV2. Our proposed hybrid method falls into the category of combining classical machine learning techniques, such as KNN, with CNNs.

Our proposed method aims to address the limitations of using deep learning methods alone, which often require large datasets. To achieve this, our method combines pretrained mask detection, landmark detection based on pretrained deep learning, robust principal component analysis for feature extraction, and a KNN classifier for face recognition. This hybrid approach allows us to effectively recognize faces while overcoming the challenges associated with using deep learning methods alone.

Methodology

This paper proposes a new methodology for recognizing faces with masks that combines deep learning-based mask detection, landmark and oval face detection, and robust principal component analysis (RPCA). The proposed methodology is designed to accurately recognize individuals wearing masks and is outlined in the following steps:

1. **Mask Detection:** The first step in the proposed methodology is to detect the presence and location of masks on a face using a pretrained SSD-MobileNetV2 model. This deep learning-based approach effectively determines whether or not a person is wearing a mask.

2. **Landmark and Oval Face Detection:** Next, landmark and oval face detection techniques are used to identify key facial features. These techniques help to accurately locate facial landmarks and obtain a better representation of the face, even when it is partially covered by a mask.

3. **Robust Principal Component Analysis (RPCA):** RPCA is used to separate occluded and non-occluded components of an image. By extracting the non-occluded components, the proposed method becomes more reliable in identifying faces with masks, as it focuses on the visible facial features.

4. **Optimization using Gazelle Optimization Algorithm:** To enhance the performance of the proposed methodology, the Gazelle Optimization Algorithm (GOA) is employed. GOA optimizes both the KNN features and the number of k (nearest neighbors) for KNN, resulting in improved accuracy and robustness.

The proposed methodology is designed to address the challenges faced by traditional face detection systems when dealing with masked faces. By combining multiple techniques and optimizing their performance, the proposed methodology allows for accurate recognition of faces with masks. The proposed methodology can be applied in a wide range of real-world scenarios, such as security systems, access control, and public health measures. The integration of deep learning-based mask detection, landmark and oval face detection, and RPCA can improve the accuracy and

reliability of masked face recognition, even in challenging and complex environments.

Pseudocode of our proposed methodology is presented as follows:

Step 1: Input Masked Face Image.
Step 2: Run Pretrained Mask Detection and Landmark Detection.
    2.1: Mask Segmentation and Conversion to Black Pixels.
Step 3: Prepare, input dataset and set the parameter.
Step 4: Normalize the Data.
Step 5: Initialize arrays for feature vectors and labels.
Step 6: Use Robust PCA for dimension reduction.
Step 7: Extract features using LBP.
    7.1: Convert binary feature selection vector to logical indexing vector.
Step 8: Split the data into training and testing sets.
Step 9: Use GOA in feature selection.
    9.1: Define the fitness function for GOA-KNN.
Step 10: Use GOA in optimizing the number of k.
Step 11: Use GOA-KNN for face recognition with optimized k value.
Step 12: Evaluate the performance of the GOA-KNN classifier.
    12.1: Train KNN classifier using training data and optimized k.
    12.2: Test the classifier.

We will explain every step of our proposed methods in the following subsections in detail. Figure 1 shows our proposed pipeline.
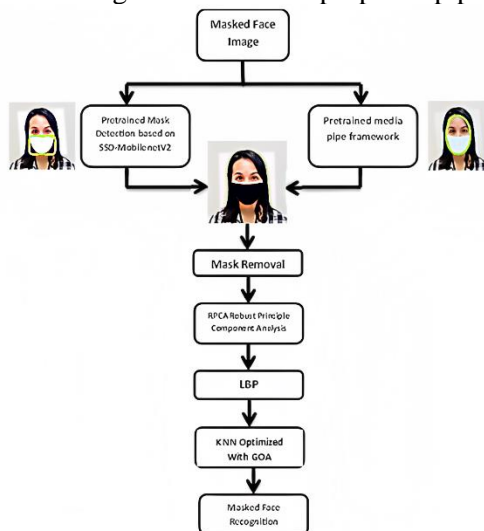

Figure 1. The Flowchart of the Proposal Method

Deep learning-based mask detection and Face Oval Detection

Facial landmark detection is a technique that identifies specific features on a person's face, such as the corners of the eyes, the tip of the nose, and the edges of the lips. These landmarks are often recognized by facial landmark detection algorithms using machine learning techniques. In our work, we use the MediaPipe framework (Lugaresi et al., 2019) to detect landmarks on face images. With the MediaPipe framework, we can detect the face oval, which is the outline of the face created by connecting the outer face landmarks, as shown in Figure 2. We also use a pretrained deep learning-based mask detection method to detect masks, which is based on SSD-MobileNetV2.
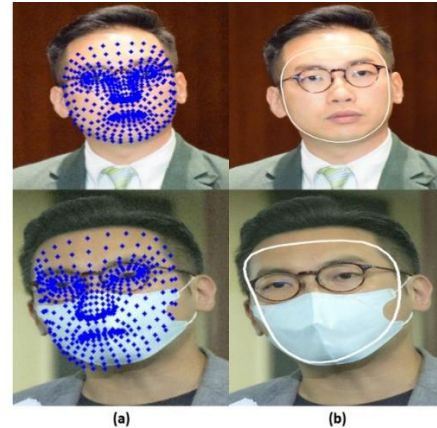

Figure 2. (a) Face Landmarks Detection and (b) Face Oval Detection.

Robust Principal Component Analysis

Principal component analysis (PCA) (Abdi, and Williams, 2010) is a well-known technique for reducing the dimensionality of data. In computer vision, it is used to represent an image with a relatively small dimensional feature vector. However, PCA is sensitive to outliers, which can distort the results. To address this issue, Cand`es et al. developed a statistical method called Robust PCA (RPCA) (Candès et al., 2011). RPCA decomposes data into its principal components, representing the underlying structure of the data, while also identifying and removing outliers and noise. This makes RPCA a powerful tool for various applications, including image and video processing, signal processing, and machine learning. In our case, the mask pixels that occlude the lower part of the face images are considered outliers and are removed by RPCA.

Before applying RPCA, the masks that cover the face images are segmented by extracting the intersection region between the bounding box surrounding the masks and the face ovals detected using the mediapipe library. The segmented masks are then converted to black pixels so as not to interfere with RPCA, as we found that colored masks are not well classified as outliers. After that, RPCA is used to obtain the low-rank matrix of face features.

In our algorithm, RPCA assumes that the matrix consisting of face image feature vectors (denoted as X) is a combination of a low-rank component representing the eigenfaces and a sparse component containing the occlusion pixels. The goal of RPCA is to factorize an input matrix X into the sum of a low-rank matrix L and a sparse matrix S such that X = L + S. This can be formulated as an optimization

$$\min_{L,S} rank\ (L) + \| S \|_0 \quad \text{subject to } L + S = X, \quad (1)$$

where $\| . \|_0$ denotes the L_0 norm. We can find the best L and S with a high probability by using a simpler way called convex relaxation, where the rank is relaxed to nuclear norm and the L_0 norm is relaxed to the L_1 norm. After convex relaxation, the equation becomes as follows,

$$\min_{L,S} \| L \|_* + \lambda \| S \|_1 \quad \text{subject to } L + S = X \quad (2)$$

where $\| . \|_*$ denotes the nuclear norm and $\| . \|_1$ denote the L_1 norm. There are several algorithms that can be used to perform RPCA, including the Principal Component Pursuit (PCP) algorithm and the Alternating Direction Method of Multipliers (ADMM) algorithm (Candès et al., 2011). These algorithms solve the optimization problem required for RPCA and can efficiently and effectively separate the low-rank and sparse components. After getting the low rank matrix L which represents the eigen faces without holes or black pixels, KNN is then used for face recognition.

K-Nearest Neighbourhood Algorithm and Gazelle Optimization algorithm for Face Recognition

Facial recognition involves analyzing specific characteristics of a person's face, such as color and texture. Texture is particularly important for biometric facial recognition because it helps the computer identify patterns in the face image. In order to extract the most important features of the face image, researchers commonly use a method called local binary pattern (LBP). LBP is effective because it works even when the face image undergoes changes due to variations in lighting, facial expressions, or pose. Accurately identifying these key parts of the face is critical for achieving precise facial recognition by computers.

Feature selection plays a crucial role in numerous machine learning and computer vision tasks, including facial recognition. The objective of feature selection is to identify the most relevant and informative features in the data while eliminating redundant and irrelevant ones that could negatively impact classifier performance. By selecting the most informative features, the classifier can better differentiate between different individuals, leading to more accurate facial recognition results. This process involves analyzing the data and selecting the features that are most relevant to the task at hand, while discarding those that are less important or redundant.

This can help reduce the dimensionality of the feature space, which can improve the accuracy and efficiency of recognition algorithms (Tubishat et al., 2020). The KNN classifier is a facial recognition method that is easy to use and computationally efficient, but its performance can be affected by the initialization of the parameter K. Therefore, it is necessary to optimize k.

Evolutionary algorithms such as GOA and Genetic Algorithm (GA) are used to select the features used for training the KNN classifier and optimize the k number because they are global metaheuristic optimization techniques that are not affected by local minima. GOA is the best choice for selecting optimal features and k.

Experimental Settings and Results

Experimental Settings

This subsection describes the experimental setup. Two datasets, a simulated masked face dataset and a real masked face dataset, are used to test the performance of different masked face recognition methods. The simulated dataset is the Labeled Face in the Wild Stimulated Masked Face Dataset (LFW-SMFD) (Dalkiran, (2020). Figure 3 shows sample images from simulated masked and non-masked faces.

Figure 3. Pairs of simulated masked and non-masked face images.

For the real dataset, we chose to use actual photographs of people wearing masks, rather than computer-generated masked face images, to provide a more realistic testing environment. We searched Google for masked pictures of well-known individuals, such as politicians and celebrities, to build our database. The photographs we selected were carefully chosen for their high quality and to avoid duplication. Figure 4 shows sample images from real masked and non-masked faces.

Figure 4. Pairs of real masked and non-masked face images.

Table 1. Performance of our proposed methods compared to the other methods in terms of Accuracy in masked face recognition.

| Reference	Dataset	Method	Recognition type	Val. Acc.
Ejaz et. al. (Ejaz et al., 2019)	ORL Face (Samaria and Harter, 1994)	PCA	Masked	72%
Ding et. al. (Ding et al., 2020)	CASIA-WebFace (Yi et al., 2014)	Latent Part Detection	Masked	94%
Rodriguez et. al. (Nieto-Rodriguez et al., 2015)	N/A	Mixture of Gaussian	Masked	95.4%
Proposed method	LFW-SMFD (Dalkiran, (2020) and real dataset	Deep learning, PCA and KNN	Masked	97.8%
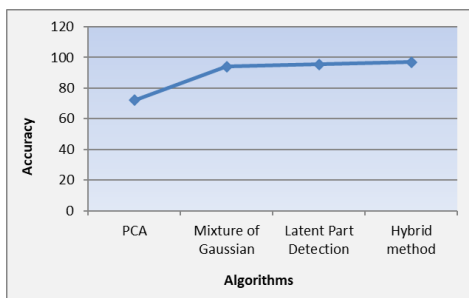
Figure 5. Analysis of the performance of the accuracy of different algorithms in masked face recognition.

Experimental Results and Discussion

In this section, the performance of our proposed algorithm is evaluated and compared to other methods, such as the PCA technique used by Ejaz et al. (Ejaz et al., 2019), the Latent Part Detection method (Ding et al., 2020), and the mixture of Gaussian method used by Rodriguez et al. (Nieto-Rodriguez et al., 2015). Table 1 and Figure 5 show the performance of our proposed method compared to these other methods in terms of accuracy in recognizing masked images. As shown in Table 1, our proposed method achieves an accuracy of 97.8% for the masked dataset, outperforming the compared methods. It is also evident that the performance of PCA alone (Ejaz et al., 2019) is the worst compared to the other results.

Table 2 and Figure 6 show the performance of our proposed method compared to other methods in terms of accuracy in recognizing unmasked images. As shown in Table 2, our proposed method achieves an accuracy of 98.9% for the unmasked dataset, outperforming the compared methods. It is also evident that the performance of PCA alone (Ejaz et al., 2019)

Table 2. Performance of our proposed methods compared to the other methods in terms of Accuracy in unmasked face image.

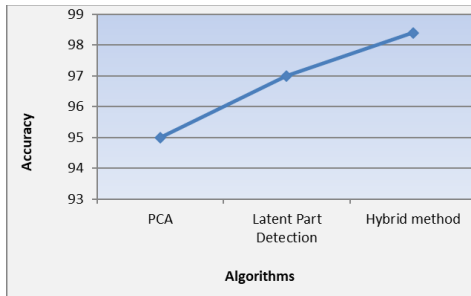| Reference	Dataset	Method	Recognition type	Val. Acc.
Ejaz et. al. (Ejaz et al., 2019)	ORL Face (Samaria and Harter, 1994)	PCA	Unmasked	95%
Ding et. al. (Ding et al., 2020)	CASIA-WebFace (Yi et al., 2014)	Latent Part Detection	Unmasked	97%
Proposed method	LFW-SMFD (Dalkiran, (2020) and real dataset	Hybrid method using deep learning, PCA and KNN	Unmasked	98.9%

Figure 6. Analysis of the performance of the accuracy of different algorithms in unmasked face recognition.

For the KNN part, the features are obtained from LBP after applying the RPCA then the KNN classifier optimized by GOA is used and it is denoted as GOA-KNN. The parameters GOA algorithm is reported in Table 3. The effectiveness of the GOA-KNN algorithm has been evaluated in comparison to conventional benchmark classifiers.

Table 3. GOA parameters

Parameter	Value
Search agents	25
Predator success rates, PSR	0.34
Top speed, S	0.88

Table 4 describes the accuracy of the proposed KNN optimized by GOA compared with unoptimized k number of KNN in the cases of using different optimization techniques such as GOA and GA for feature extraction.

Table 4. Comparative analysis of accuracy of proposed method with existing benchmark algorithms in case of unmasked dataset.

Type of Features	KNN Acc.	GOA-KNN Acc.
Actual features	89 %	93%
GA	94 %	96 %
GOA	95 %	98.9 %

The results show that GOA-KNN outperforms KNN in all scenarios, achieving a higher classification accuracy. For example, when using actual features, KNN achieved an accuracy of 89%, while GOA-KNN achieved an accuracy of 93%. When using GA for feature selection, KNN achieved an accuracy of 94%, while GOA-KNN achieved an accuracy of 96%. When using GOA for feature selection, KNN achieved an accuracy of 95%, while GOA-KNN achieved an accuracy of 98.9%, which is the highest accuracy among all methods.

The results demonstrate that GOA-KNN is a more effective algorithm for masked face recognition, achieving higher accuracy

compared to KNN, especially when GOA is used for feature selection and optimizing the value of k.

Future work

In future work, our proposed method could be extended to handle other types of occlusions, such as sunglasses, scarves, and hats, which can also pose challenges to face recognition systems. Additionally, incorporating other biometric modalities, such as voice and fingerprint recognition, could further improve the accuracy and reliability of the system. Another area for future research is to explore the privacy implications of masked face recognition. As masks have become a common part of daily life, concerns about the impact of facial recognition technology on privacy have increased.

Our proposed method relies on face recognition, which raises concerns about the potential for misuse and abuse of the technology. Therefore, future research could focus on developing ethical guidelines and regulations for the use of masked face recognition technology.

Conclusion

The need for effective masked face recognition technologies has become essential due to the widespread use of face masks in various industries and jobs. In this paper, we introduced a new method that combines deep learning-based mask detection, landmark and oval face detection, and robust principal component analysis (RPCA) for accurate masked face recognition. Our method uses a pretrained ssd-MobileNetV2 model for mask detection and RPCA to separate occluded and non-occluded components of an image. To optimize the performance of our method, we used the Gazelle Optimization Algorithm (GOA) to optimize both the KNN features and the number of k for KNN. Experimental results showed that our method outperformed existing methods in terms of accuracy and robustness to occlusion, achieving a recognition rate of 97%, significantly higher than state-of-the-art methods. Overall, our method represents a significant improvement over existing methods for masked face recognition, providing high

accuracy and robustness to occlusion.

Authors' Contributions

This work was carried out in collaboration among all authors. All Authors designed the study, performed the statistical analysis and wrote the protocol. Authors ME, TMM and TAEH managed the analyses of the study, managed the literature searches and wrote the first draft of the manuscript. All authors read and approved the final manuscript.

Data availability

The data that support the findings of this study are available in https://www.kaggle.com/datasets/muhamm eddalkran/lfw-simulated-masked-face-dataset

Declaration of competing interest

The authors declare that there is no conflict of interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Statement: "This article does not contain any studies with human participants or animals performed by any of the authors."

References

Jain, A., Bolle, R., and Pankanti, S. (1996). Introduction to biometrics. Springer..

Sasirekha, K. and Thangavel, K. (2019). Optimization of K-nearest neighbor using particle swarm optimization for face recognition. Neural Computing and Applications, Vol. 31, pp. 7935-7944.

Zhao, W., Zhu, X., Shi, H., Zhang, X.-Y., and Lei, Z. (2022). Consistent Sub-Decision Network for Low-Quality Masked Face Recognition. IEEE Signal Processing Letters, Vol. 29, pp. 1147-1151

Adhikarla, E. and Davison, B. D. (2021). Face mask detection on real-world Webcam images. In Proceedings of the Conference on Information Technology for Social Good, pp. 139-144

Ding, F., Peng, P., Huang, Y., Geng, M., and Tian,

Y. (2020). Masked face recognition with latent part detection. In Proceedings of the 28th ACM international Conference on multimedia, pp. 2281-2289.

Vu, H. N., Nguyen, M. H., and Pham, C. (2022). Masked face recognition with convolutional neural networks and local binary patterns. Applied Intelligence, Vol. 52, pp. 5497-5512

Aswal,V., Tupe,O., Shaikh,S., and Charniya,N.N.(2020).Single camera masked face identification.In 2020 19th IEEE international conference on machine learning and applications (ICMLA),pp.57-60

Kocacinar, B., Tas, B., Akbulut, F. P., Catal, C., and Mishra, D. (2022). A real-time cnn-based lightweight mobile masked face recognition system. Ieee Access, Vol. 10, pp. 63496-63507..

Qi, C. and Yang, L. (2020). Face recognition in the scene of wearing a mask. In 2020 International Conference on Advance in Ambient Computing and Intelligence (ICAACI), pp. 77-80.

Singh, S., Ahuja, U., Kumar, M., Kumar, K., and Sachdeva, M. (2021). Face mask detection using YOLOv3 and faster R-CNN models: COVID-19 environment. Multimedia Tools and Applications, Vol. 80, pp. 19753-19768

Zhu, R., Yin, K., Xiong, H., Tang, H., and Yin, G. (2021). Masked face detection algorithm in the dense crowd based on federated learning. Wireless Communications and Mobile Computing, Vol. 2021, pp. 1-8.

Jignesh Chowdary, G., Punn, N. S., Sonbhadra, S. K., and Agarwal, S. (2020). Face mask detection using transfer learning of inceptionv3. In Big Data Analytics: 8th International Conference, BDA 2020, Sonepat, India, December 15–18,

Loey, M., Manogaran, G., Taha, M. H. N., and Khalifa, N. E. M. (2021). A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic. Measurement, Vol. 167, p. 108288.

Suresh, K., Palangappa, M., and Bhuvan, S. (2021). Face mask detection by using optimistic convolutional neural network. In 2021 6th International Conference on Inventive Computation Technologies (ICICT), pp. 1084-1089.

Lodh, A., Saxena, U., Motwani, A., Shakkeera, L., and Sharmasth, V. Y. (2020). Prototype for integration of face mask detection and person identification model–COVID-19. In 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), pp. 1361-1367.

Rusli, M. H., Sjarif, N. N. A., Yuhaniz, S. S., Kok, S., and Kadir, M. S. (2021). Evaluating the masked and unmasked face with LeNet algorithm. In 2021 IEEE 17th International

Colloquium on Signal Processing & Its Applications (CSPA), pp. 171-176.

SALEH, N. A., ERTUNÇ, H. M., SALEH, R. A., and RASSAM, M. A. (2021). A simple mask detection model based on a multi-layer perception neural network. In 2021 International Conference of Technology, Science and Administration (ICTSA), pp. 1-5.

Wu, G. (2021). Masked face recognition algorithm for a contactless distribution cabinet. Mathematical problems in engineering, Vol. 2021, pp. 1-11.

Oumina, A., El Makhfi, N., and Hamdi, M. (2020). Control the covid-19 pandemic: Face mask detection using transfer learning. In 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), pp. 1-5.

Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., et al. (2019). Mediapipe: A framework for building perception pipelines. arXiv preprint arXiv:1906.08172.

Abdi, H. and Williams, L. J. (2010). Principal component analysis. Wiley interdisciplinary reviews: computational statistics, Vol. 2, pp. 433-459.

Candès, E. J., Li, X., Ma, Y., and Wright, J. (2011). Robust principal component analysis? Journal of the ACM (JACM), Vol. 58, pp. 1-37.

Tubishat, M., Alswaitti, M., Mirjalili, S., Al-Garadi, M. A., and Rana, T. A. (2020). Dynamic butterfly optimization algorithm for feature selection. IEEE Access, Vol. 8, pp. 194303-194314.

Dalkiran, M. (2020). LFW Simulated Masked Face Dataset| Kaggle.

Ejaz, M. S., Islam, M. R., Sifatullah, M., and Sarker, A. (2019). Implementation of principal component analysis on masked and non-masked face recognition. In 2019 1st international conference on advances in science, engineering and robotics technology (ICASERT), pp. 1-5.

Nieto-Rodriguez, A., Mucientes, M., and Brea, V. M. (2015). System for medical mask detection in the operating room through facial attributes. In Pattern Recognition and Image Analysis: 7th Iberian Conference, IbPRIA 2015, Santiago de Compostela, Spain, June 17-19, 2015, Proceedings 7, pp. 138-145.

Samaria, F. S. and Harter, A. C. (1994). Parameterisation of a stochastic model for human face identification. In Proceedings of 1994 IEEE workshop on applications of computer vision, pp. 138-142.

Yi, D., Lei, Z., Liao, S., and Li, S. Z. (2014). Learning face representation from scratch. arXiv preprint arXiv:1411.7923.

<div dir="rtl">

الملخص العربي

عنوان البحث: نموذج مبتكر للتعرف على الوجوه المقنعة باستخدام مزيج من نموذج مدرب مسبقا لكشف القناع وتحليل المكونات الرئيسية (PCA)، ومصنف KNN ومحسّن GOA

محمد ايمان محمد طه *`¹`، طارق مصطفى محمود`²`، طارق عبد الحفيظ `³، ⁴`

`¹` قسم علوم الحاسب ــ كلية الحاسبات والذكاء الاصطناعي ــ جامعة بنى سويف ــ مصر

`²` كلية الحاسبات والذكاء الاصطناعي ــ جامعة مدينة السادات ــ مصر

`³` قسم علوم الحاسب ــ كلية العلوم ــ جامعة المنيا ــ مصر

`⁴` وحدة علوم الحاسب ــ جامعة دراية ــ محافظة المنيا ــ مصر

أصبح استخدام أقنعة الوجه شائعاً في مجموعة واسعة من الصناعات، بما في ذلك الرعاية الصحية وخدمات الطعام والبناء والضيافة والنقل والتعليم والسلامة العامة. لتجاوز هذا التحدّي، ظهرت التعرّف على الوجوه المقنعة كتقنية حيوية في السنوات الأخيرة. من خلال استخدام خوارزميات متقدّمة وتقنيات التعلّم العميق، يتيح التعرّف على الوجه المقنعة التعرّف والمصادقة الدقيقة على الأفراد حتى في السيناريوهات التي يتم فيها ارتداء الأقنعة. تقدّم هذه الورقة طريقة جديدة للتعرّف على الوجوه التي ترتدي الأقنعة. تدمج الطريقة المقترحة كشف الأقنعة القائم على التعلّم العميق، وكشف نقاط الوجه والوجه البيضاوي، وتحليل المكوّنات الرئيسية القوي (RPCA) للتعرّف والمصادقة الدقيقة على الأفراد الذين يرتدون الأقنعة. يتم استخدام نموذج ssd-MobileNetV2 المدرّب مسبقاً للكشف عن وجود الأقنعة وموقعها على الوجه، بينما يتم استخدام كشف نقاط الوجه والوجه البيضاوي للتعرّف واستخراج السمات الوجهية الهامة. يتم تطبيق RPCA لفصل المكونات المعوقة وغير المعوقة في الصورة، مما يجعل الطريقة أكثر موثوقية في التعرّف على الوجوه التي ترتدي الأقنعة. ولتحسين أداء الطريقة المقترحة، يتم استخدام خوارزمية تحسين الغزال (GOA) لتحسين كل من ميزات KNN وعدد k لـ KNN. تشير النتائج التجريبية إلى أن الطريقة المقترحة تفوق الطرق الموجودة من حيث الدقة والقوة في التعرّف على الوجوه المعوقة، حيث تحقق معدل التعرّف ٩٧٪. وهذا يمثل تحسيناً كبيراً على الطرق الموجودة للتعرّف على الوجوه المقنعة. تتميّز الطريقة المقترحة بإمكانية تطبيقها في مجموعة واسعة من السيناريوهات الحقيقية، مثل أنظمة الأمن والتحكم في الوصول وإجراءات الصحة العامة.

</div>