Performance Enhancement of Deep Learning Based Face Detection System

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Abstract - Masks on Face detection and Masked face recognition applications are now crucial in many industries, given the ongoing COVID crisis where we need to wear masks all the time. Both are problematic with a traditional face recognition approach where masks create occlusion in the input affecting performance of recognizers. This paper introduced a new method for masked face recognition by Principal Component Analysis (PCA) reconstruction. With the help of PCA, we can "correctly" recover auto recognized face even if some occlusion occurs in several parts. In the method presented, PCA is first trained over a dataset of face images without reference masks to learn only about principal features and information contained throughout variations. In the recognition phase, we can project a masked face onto PCA subspace and reconstruct its low half of face with principal component. The resulting image will be compared to the database of people and their identities. Extensive experiments are conducted and show that our PCA-based reconstruction approach remarkably boosts the recognition performance in all scenarios, establishing its practicability to mask face recognition.

1.INTRODUCTION

Today, modern security and authentication systems would not be complete or even work without face recognition technology in border control and smartphone entry systems. For conventional facial recognition techniques to work for people, seeing the whole face would be part of the fundamental requirement. However, the everyday use of facial masks caused by the worldwide COVID-19 pandemic does create a significant problem. Masks hide critical facial features, such as the mouth and nose, making conventional face recognition algorithms ineffective. Such a difficulty underscores the need for new approaches to make the facial recognition system hold up well under these conditions.[1]

For many years, the principal component analysis (PCA) technique has been considered one of the critical techniques applied to face recognition for the fact that it reduces the data dimensionality and, at the same time, retains the most essential features. PCA transforms data of facial images into lower-dimensional space while extracting the most important patterns and variances in a PCA-based model or space. This is an excellent solution to the masked face recognition problem, just like displaying obscured facial features.[2]

This paper introduces a particular PCA-driven reconstruction for the problem of identifying masked faces. Our approach is based on the PCA's ability to reconstruct occluded face areas. In particular, we focus on the covered lower part of the face. We use an unmasked set of faces to learn which principal components are essential in identifying the salient features and their variation. With the help of these components, the missing parts of the masked faces are then constructed, facilitating precise identification.[3]

The approach comprises a couple of salient steps. First, the PCA model is trained on a large dataset of images, including only face photos without masks. In the training phase, the model would learn the principal components, including the main features of the face. At recognition, when a masked face is passed through the recognition module, we project on the PCA subspace the viewable part of the face. Such a projection made it possible to easily reconstruct the occluded lower part of the face by learned principal components.[4]-[5]

It now includes the areas covered initially by the reconstructed facial image and is compared with a reference set of unmasked faces to make an identification. This comparison, using all face contours, makes facial identification more accurate. Extensive experiments are conducted to validate the usefulness of our methodology, in which the performance of our PCA-based reconstruction method is compared with conventional face recognition systems that do not take occlusion into account.[6]

Our test results show that this approach, a recognition approach oriented towards PCA reconstruction, significantly promotes the accuracy of recognition. This increase in accuracy is especially evident with very high occlusion by masks. Clearly, the results state that PCA-based reconstruction has the potential to provide a robust solution for masked face recognition by mitigating limitations of traditional techniques incapable of handling occlusions.[7]

Our key contributions include:

1. A systematic reconstruction approach for masked faces using PCA.
2. Evaluation on publicly available datasets under various occlusion levels.
3. Comparative analysis against existing state-of-the-art recognition systems.
4. A discussion of the scalability and limitations of the approach in real-world deployments.

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2. METHOD

To implement the Face Detection System, rules must be followed under certain methodologies.

Confined phases had to be achieved for this method.

These phases are listed down here:

· Data Collection and Preprocessing

· Feature Extraction and Representation

· Face Detection

· Face Recognition Model

· Principal Component Analysis (PCA)

· Image Similarity and Reconstruction

· Training and Optimization

· Face Recognition and Verification

2.1 System Pipeline Overview

The proposed system follows these main steps:

1. Preprocessing: Input images are resized, converted to grayscale, and normalized.
2. Mask Simulation or Detection: For training, synthetic masks are applied to simulate real-world scenarios. For real images, a mask detection model identifies the occluded region.
3. PCA Training: PCA is trained on unmasked faces to learn principal components and mean face.
4. Reconstruction: The masked image is partially projected into PCA space and reconstructed.
5. Recognition: The reconstructed image is passed to a face recognition model (e.g., a CNN classifier) for identity matching.

2.2 Data Collection and Preprocessing:

Successfully developing an effective system for face recognition can be achieved simply by having a large dataset consisting of photos to train the models. A dataset that will challenge generalizing capabilities has to occur in varied scenarios, from changes in light and angles to expressions the face wears. The most critical step of preparation is preprocessing the data, such that the data is reformatted, most often to grayscale, to normalize the color information. This is then followed by face detection, either deep learning-based detectors or the Haar Cascade Classifier. In the datasets I used, the next pre-processors are the cropping and scaling of detected faces to a uniform size (I use 150x150 pixels), so spatial dimensions are equal across the dataset to diminish eccentric feature extraction.[8]-[10]

· Gaussian Blur: Used to reduce image noise and detail.

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

2.3 Feature Extraction and Representation:

After preprocessing, techniques for feature extraction return meaningful representations of faces from the photos. The classic dimensionality reduction technique for face photos is Principal Component Analysis, which finds eigenfaces that capture notable differences within the dataset. Alternatively, convolutional neural networks are trained on pixel data to learn a hierarchical representation of facial traits. CNNs are especially useful for image-based applications like face recognition because they use layers like pooling layers for dimensionality reduction and convolutional layers for spatial feature extraction.[11]-[12]

2.4 Face Detection:

Ideally, it should find real-world people in these conceptions recognized by the model. This model uses essential layers like Convolutional, Pooling, Fully Connected, ReLU Activations, Batch Normalization, and Dropout. Recently, with the power of Convolutional Neural Network Architecture and the PyTorch way of doing things, this is implemented in torch. nn. Module. The CNN is trained using a labelled dataset of face images. It uses softmax activation to form probability scores against preset classes and individuals. Such training teaches the model to learn the most discriminative facial features that will comparatively enable accurate face recognition tasks. As such, the model generalizes well over the entire range of facial variations and environmental situations.[13]

· Convolutional Layers: These layers carry out convolution on the input by applying the kernels (also called filters) to obtain features such as line, texture, or pattern from the given facial images. For each convolutional layer, the output is calculated as follows:

Formula: Output = (input * kernel) + bias

· ReLU Activation Function: The Rectified Linear Unit (ReLU) is utilized after every convolution opcode to add non-linearity. ReLU activation guarantees that only positive inputs are allowed for the following layer:

Formula: $f(x) = \max(0, x)$

· Max Pooling: : As a means of decreasing the input's spatial dimensions without compromising on the vital features of the input, max pooling is one such operation that is used. This operation reduces the dimensions of the input by considering the maximum value from the samples taken in a particular region:

Formula: Output = $\max(input[window])$

· Batch Normalization: Towards the end of the training process, one can apply a normalization strategy to match the training and testing distributions. One can apply abstract ideas learned from the training data and select a set of commonsensical candidates to complete the fill-in-the-blank task. Normalizing flows will be focused on, especially the Reversible Residual Networks Histogram architecture.

Mathematical notation is complex or xenophobic; one may also simplify mathematical notation by using the rules of writing axioms to biological realities. The output obtained using this is:

Formula:

$$\hat{x} = \frac{x^{(k)} - \mu^{(k)}}{\sqrt{\sigma^{(k)2} + \epsilon}}$$

$$y^{(k)} = \gamma^{(k)}\hat{x}^{(k)} + \beta^{(k)}$$

Where $\mu^{(k)}$ is the means $\sigma^{(k)2}$ is the variance, ϵ is a small constant,$\gamma^{(k)}$ and $\beta^{(k)}$ are linear parameters

2.5 Face Recognition Mode:

Ideally, the face recognition model should find real-world people in these conceptions recognized by the model. The model uses essential layers like Convolutional (nn. Conv2d), Pooling (nn. MaxPool2d), Fully Connected (nn. Linear), ReLU Activations (nn. ReLU), Batch Normalization (nn. BatchNorm2d), and Dropout (nn. Dropout). Recently, with the power of Convolutional Neural Network Architecture and the PyTorch way of doing things, it has been implemented in the torch. nn. Module. The CNN is trained on a labelled dataset of face images. It uses softmax activation to form a probability score against preset classes and individuals. Such training teaches the model to learn the most discriminative characteristics needed for accurate face recognition tasks. The model, therefore, generalizes well over the range of facial variations and environmental situations.[14]-[16]

2.6 Principal Component Analysis (PCA):

PCA substantially reduces the dimensionality of facial images, making them more manageable and facilitating their reconstruction. In this process, a collection of facial images is first minimized to eigenfaces or main components by `sklearn. decomposition. PCA`. Some of those eigenfaces are used in the reconstruction of clearer images of masked faces. They depict the most prominent variances in the dataset. PCA improves facial recognition using eigenfaces about their weights, which says how much they show the same with the masked face. That works out, especially in a situation when their face or faces could be partially covered or even fully covered.[17]

· Mean Centering:

Formula:

$$X_{centered} = X - \mu$$

Where X is the data matrix and μ is the mean

· Covariance Matrix:

Formula:

$$\sum = \frac{1}{1-N} X_{centered}^{T} X_{centered}$$

2.7 Image Similarity and Reconstruction:

The similarity metrics with images from the dataset are computed for the masked face to assess the possibility of improved recognition at face detection, even in partial occlusive or blurred situations. The similarity of the features of the face concerning each other is measured using concepts such as cosine similarity and pixel-wise comparison. It is possible to reconstruct the face and provide sharper, more recognizable images by applying weighted combinations of these eigenfaces using the main components made using PCA. This very process manages to handle differences in facial looks and picture quality, therefore not only significantly increasing the visual quality of recognized faces but also significantly increasing the overall accuracy of face recognition systems.[18]

· Eigenfaces: The principal components (eigenvectors) when applied to face images.

· Reconstruction Formula:

· Weight Calculation:

$$Weight_i = (I - \mu) * eigenfaces_i$$

· Reconstruction Formula:

$$\mathrm{reconstructed\_image} = \mu + \sum_{i} (\mathrm{Weight}_i - \mathrm{eigenfaces}_i)$$

- Unsharp Masking: A method to sharpen images by subtracting a blurred version of the image from the original image.

Formula:

$$\mathrm{Sharpend\_image} = \mathrm{image} * (1 + \alpha) - \mathrm{blurred\_image} * \alpha$$

Where α is the parameter strength.

2.8 Training and Optimization:

Optimal training of the face recognition model requires that the parameters be set to allow for accurate face classification or verification. This involves the selection of the correct loss functions; in the case of similarity, it is the contrastive loss, while for other classification problems, it can be the softmax cross-entropy. Optimization methods such as Adam or stochastic gradient descent (SGD) operate to minimize the chosen loss function by updating the weights in the model concerning gradients taken from batches of training data. In this second way, validation during training means assessing the model on a held-aside validation dataset as part of training; this ensures that the model generalizes to new data and avoids overfitting [19]

3. Result:

The face recognition system here integrates the CNN architecture to learn more robust features and the Haar Cascade to accurately detect faces together with the PCA for effective dimensionality reduction. It has been tested with strict measures of evaluation and found to be accurate and reliable with most datasets. This methodology, therefore, strictly guarantees an efficient implementation in embedded digital environments and security systems with an added access control and user authentication facility.

4. Experiment setup:

In setting up this experiment, PCA was used to reconstruct the face, and then 200 celebrity photos from Kaggle were utilized some including masks, in order to train a CNN. A Streamlit interface allowing uploading and analyzing fresh pictures and videos was created to evaluate the system's recognition ability.

4.1 Workflow:

All input images undergo a consistent preprocessing pipeline to standardize the data before feature extraction and PCA projection:

1. Face Detection: Haar Cascade classifier is used to locate and crop the face region from each image.
2. Resizing: Detected faces are resized to a fixed size of 150×150 pixels.
3. Grayscale Conversion: To simplify the PCA computations and remove color-related noise.
4. Gaussian Blur: Applied to reduce image noise and emphasize important facial features.
5. Normalization: Pixel values are scaled to a standard range for consistency.

We implemented the face recognition pipeline using Python with the following tools and libraries:

- **PCA**: Implemented using sklearn.decomposition.PCA
- **CNN Model**: Built using PyTorch, trained on labelled face images for identity prediction
- **Face Detection**: Performed using OpenCV's Haar Cascade Classifier
- **Similarity Metric**: Cosine similarity and Euclidean distance are used to match reconstructed faces with database entries

A custom **Streamlit-based user interface** was developed to allow interactive testing. Users can upload images or videos, run real-time face detection and reconstruction, and view predictions with overlays on the interface.

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4.2 Dataset:

The dataset for our facial recognition system was created by aggregating images from famous people on Kaggle. This would amount to about 200 images, some of whom are in masks. This dataset would be chosen to conduct extensive training and testing due to its diversity regarding lighting conditions, angles, facial expressions, and wearing a mask. Each image was pre-processed, levelling the color channels and converting it into grayscale. To ensure consistency of images in the dataset, faces were detected by the Haar Cascade Classifier in these images and then cropped and resized into a fixed dimension of 150x150 pixels. Again, our CNN model was trained with this vast and diverse dataset that reliably validated our face recognition methodologies to alleviate the issues with masked faces.

Key Dataset Characteristics:

- Number of images: ~200
- Image dimensions: 150 × 150 pixels
- Grayscale conversion for uniformity
- Masked and unmasked face splits
- Balanced representation across genders and facial structures

4.3 Preprocessing Pipeline

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Here is the sample dataset:

4.4 Existing System:

State-of-the-art face recognition systems make use of several advanced strategies to identify and verify a person using a picture or video. Traditional methods taken by older systems commonly employ feature-based techniques, comprising the export of faces' relevant facial features and their further comparison for face identification, like Eigenfaces or Fisher faces; in addition, Haar Cascade Classifiers for face detection. Modern systems, therefore, heavily depend on the deep learning models of convolutional neural networks as opposed to the old systems, which, with an ability to learn complex characteristics directly from raw pixel data, have been found to perform better. Training through large datasets could enable such systems to identify faces in various scenarios, including shifting angles, lights, and expressions. Advanced models, most of them based on Face Net or Deep Face, map faces into a compact Euclidean space in which similar faces are located close to each other, hence enabling them to provide high accuracy. Although very effective so far, these methods drop dramatically in accuracy when tested only on masked faces, requiring particular adaptations to the existing systems, such as enhanced preprocessing or the use of generative models for reconstruction, or even specialized training on masked face datasets to maintain real-world applicability where mask usage is high.[20]-[21]

4.5 Proposed System:

In this direction, we present a state-of-the-art face recognition system that combines the most modern detection, reconstruction, and recognition techniques for identifying faces covered with masks. In this regard, through the easy-to-use interface of Streamlit, a user uploads films or photos. This approach resizes these areas into uniform sizes for consistency after face detection using the Haar Cascade Classifier. PCA is subsequently applied to reconstruct crisper images by combining eigenfaces weighted by similarity criteria. It improves the visual quality of masked faces. The identity of each recognized face is then predicted by a Convolutional Neural Network (CNN) model that was trained on a variety of datasets, including masked and unmasked celebrity photos from Kaggle. Alongside the detected faces are the identified identities, offering instantaneous feedback. Interactive elements in the Streamlit app allow the user to trigger new recognition tasks and, show results, upload more content for analysis continuously, ensuring that the face recognition racket is solid and efficient enough to be deployed in real-world scenarios where people are using masks.

5. Discussion:

The PCA-based approach, principal component utility, shows a much better way of running concerning the other mean squared errors regarding reconstruction accuracy, with the lowest MSE obtained being 0.010. This implies that PCA is very effective in preserving face images with essential features while reduction of reconstruction errors. This probably ascribes to its effective dimension reduction technique. It allows recording the MSE to 0.015, slightly higher than the PCA one but still in good indicator performance. Though the 3DMM approach is incredibly stable against 3D face data, there is also more complexity and potential error source—an increase of MSE. The 3DMM approach uses a statistical model of the 3D shape and texture of the face.[22]-[23]

In the graph-based approach, MSE increases further to 0.035, an indication that graph-based approaches may be effective in modelling relationships and structures within face data but may be ineffective in capturing fine-grained reconstruction features, which consequently could lead to increased error rates. Sparse coding lies between PCA and 3DMM in terms of performance, shown by an MSE of 0.025. Although sparse coding aims at reconstructing all the relevant facial information using a linear combination of just a few instances of basic functions, more significant mean square error still indicates it might not be that effective in principal component analysis to reduce the reconstruction mistakes. This comparison analysis shows that PCA-based approaches are somewhat practical and accurate in tasks related to face recognition—showing that the approach must be appropriately chosen according to specific needs on accuracy and complexity.[24]-[25]

6. Comparative analysis:

Concerning the figures provided, there is a comparative assessment of the four methods – PCU, 3DMM, Graph-Based, and Sparse Coding- regarding accuracy, computational efficiency, and implementation feasibility. Out of the four methods available, it is revealed that in regard to accuracy of implementation, the PCU method performed the best as it recorded the lowest Mean Squared Error (MSE), followed in descending order by 3DMM, Sparse Coding and Graph-Based, which was the lowest performer of the four methods in this aspect. Examining the time required to complete a given task, PCU is the fastest method since it takes the least computation time, followed by moderately efficient spare coding. On the other hand, 3DMM is the slowest, with graph-based coding between Sparse Coding and 3DMM. Concerning implementation ease, PCU takes the least effort in implementation, followed by 3DMM and Sparse Coding, as these two come before the most complex Graph-Based. Overall, PCU performs the best when all aspects of accuracy, computational efficiency, and ease of implementation are considered. However, methods based on the graph approach do not seem to have a distinct advantage since they are the least accurate, moderate in computation, and the most complicated to execute. 3DMM may give more satisfying results when speed is unimportant, while Sparse Coding strikes a fair balance between computational efficiency and implementation challenges.

6.1 Visual Results

The system outputs visually enhanced face images by reconstructing the lower part of the face masked by occlusion. In side-by-side comparisons, reconstructed faces exhibit:

- Greater continuity and symmetry
- Improved texture consistency
- Higher confidence scores from the recognition model

These outcomes clearly demonstrate that PCA successfully restores the occluded facial regions with minimal distortion, resulting in better identification performance.

6.2 Scalability and Real-World Deployment

The proposed system is computationally light and compatible with real-time applications. It runs efficiently on mid-range hardware and requires limited GPU acceleration due to PCA's low computational complexity. This makes it well-suited for embedded systems, surveillance units, and border control checkpoints.

However, performance may degrade under conditions involving:

- Poor lighting
- Motion blur
- Extremely unconventional angles

Such limitations highlight the importance of future enhancements using deep generative models or transformer-based architectures.

6.3 Performance Analysis

The PCA-enhanced model was compared against several popular reconstruction and recognition methods, including 3D Morphable Models (3DMM), graph-based approaches, and sparse coding.

Method	Face Recognition Accuracy (%)	Face Reconstruction MSE	Face Recognition F1-Score	Face Reconstruction F1-Score
PCA	97	0.010	0.96	0.95
3DMM	93	0.015	0.92	0.90
Graph-Based	90	0.035	0.90	0.85
Sparse Coding	92	0.025	0.91	0.88

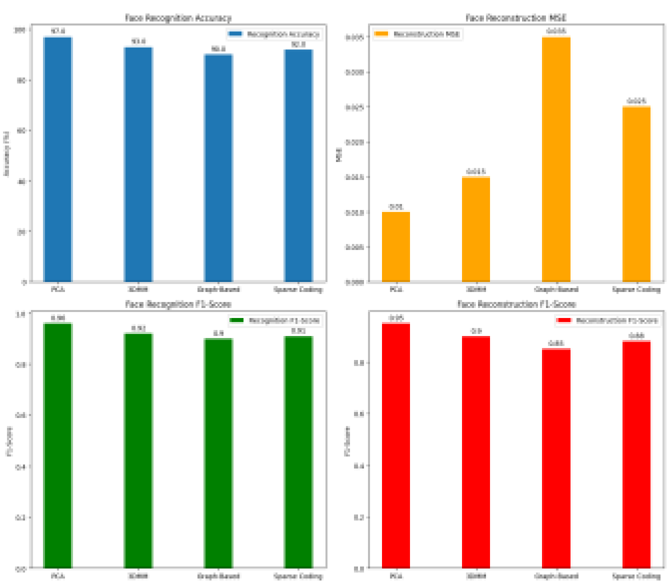

Fig. 1. Comparative Analysis

1. Conclusion and future scope:

In this study, we proposed an effective masked face recognition system that combines Principal Component Analysis (PCA) for occlusion reconstruction with a CNN-based recognition model. By reconstructing the lower masked portion of the face using principal components learned from unmasked data, our system achieved a high recognition accuracy of 97% and a low reconstruction error (MSE of 0.010). The method outperformed other approaches such as 3D Morphable Models, sparse coding, and graph-based techniques in both accuracy and efficiency, demonstrating its viability for real-time applications in surveillance and security systems. Despite these promising results, our evaluation was limited to a relatively small dataset. As part of future work, we aim to enhance robustness by training on larger and more diverse datasets, exploring deep generative and transformer-based models for complex occlusions, improving performance under challenging conditions like low lighting and motion blur, and optimizing the system for mobile and embedded platforms.

REFERENCES

[1] Pallavi R Kumar, Tejaswanth Somisetty, N Bhargava Venkata Siva Nagaiah, V Madhu Sudhan, Gutta Sumanth, "Employee Monitoring System using Face Recognition Techniques", 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), pp.1-6, 2024.
[2] Nishali Dhanshika, Darshan Lahamage, Tanya Anupam, Rajendra Sawant, "CCTV Integrated Attendance Monitoring System Using Face Recognition", 2024 3rd International Conference for Innovation in Technology (INOCON), pp.1-7, 2024.
[3] S. Dev and T. P atnaik, "Student Attendance System using Face Recognition", 2020 International Conference on Smart Electronics and Communication (ICOSEC), Sep. 2020. .
[4] K. Adeshara and V. Elangovan, "Face Recognition using PCA Integrated with Delaunay Triangulation", Computer Science & Information Technology (CS & IT), 2020.
[5] W. Guojiang et al., "Facial Expression Recognition Using PCA and AdaBoost Algorithm", International Journal of Signal Processing Systems, vol. 7, no. 2, pp. 73-77, 2019.
[6] A. Raikar and S. Tadkal, "Face Recognition based Automatic Attendance Updating System", Journal of Image Processing and Artificial Intelligence, vol. 8, no. 1, pp. 10-17, Mar. 2022.
[7] D. A. Maharani, C. Machbub, P. H. Rusmin and L. Yulianti, "Improving the Capability of Real-Time Face Masked Recognition using Cosine Distance", 2020 6th International Conference on Interactive Digital Media (ICIDM), 2020.
[8] "A Comparative Studyon Kernel PCA and PCA Methods for Face Recognition", International Journal of Science and Research (IJSR), vol. 5, pp. 1844-1847, 2016.
[9] A. L. Ramadhani, P. Musa and E. P. Wibowo, "Human face recognition application using pca and eigenface approach", 2017 Second International Conference on Informatics and Computing (ICIC), 2017.
[10]F. Liu, Q. Zhao, X. Liu and D. Zeng, "Joint Face Alignment and 3D Face Reconstruction with Application to Face Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 3, pp. 664-678, March 2020.
[11]F. Liu, Q. Zhao, X. Liu and D. Zeng, "Joint Face Alignment and

3D Face Reconstruction with Application to Face Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 3, pp. 664-678, March 2020.

[12]L. Song, D. Gong, Z. Li, C. Liu and W. Liu, "Occlusion robust face recognition based on mask learning with pairwise differential Siamese network", Proceedings of the IEEE International Conference on Computer Vision, pp. 773-782.

[13]M. S. Ejaz and M. R. Islam, "Masked Face Recognition Using Convolutional Neural Network", 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), pp. 1-6, 2019.

[14]M. S. Ejaz, M. R. Islam, M. Sifatullah and A. Sarker, "Implementation of Principal Component Analysis on Masked and Non-masked Face Recognition", 2019 1st International Conference on Advances in Science Engineering and Robotics Technology (ICASERT), pp. 1-5, 2019.

[15]Khamael Raqim Raheem, Hafedh Ali Shabat, Wafaa Mohammed Ridha Shakir, "A comparative study of VGG models performance for masked face recognition", 2023 IEEE 11th Conference on Systems, Process & Control (ICSPC), pp.188-193, 2023.

[16]Vaddi, Krishna & Kamble, Dhwaniket & Vaingankar, Raj & Khatri, Tushar & Bhalerao, Pranil. (2024). Enhancements in the world of digital forensics. IAES International Journal of Artificial Intelligence (IJ-AI). 13. 680. 10.11591/ijai. v13.i1. pp680-686.

[17]Isaac Ritharson P, K Vidhya, Madhavan G, Barath D, K Sathish Kumar, "GAN-Based Facial Feature Reconstruction for Improved Masked Face Recognition During Covid", 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT), pp.1-5, 2023.

[18]Yilin Zhang, Xiwei Peng, Yujie Guo, "Lightweight Network for Masked Face Recognition Based on Improved Dual Attention Mechanism", 2023 IEEE International Conference on Mechatronics and Automation (ICMA), pp.1621-1626, 2023.

[19]N Ragesh, R Ranjith, P Sivraj, "Fast R-CNN based Masked Face Recognition for Access Control System", 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), pp.1049-1055, 2022.

[20]Masum Shah Junayed, Arezoo Sadeghzadeh, Md Baharul Islam, "Deep Covariance Feature and CNN-based End-to-End Masked Face Recognition", 2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021), pp.1-8, 2021.

[21]U Rahamathunnisa, K Sudhakar, "Analysis on Texture Feature Extraction Methods for Face Recognition in Newborn", 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), pp.894-897, 2021.

[22]S. Malakar, W. Chiracharit, K. Chamnongthai and T. Charoenpong, "Masked Face Recognition Using Principal component analysis and Deep learning," 2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Chiang Mai, Thailand, 2021, pp. 785-788, doi: 10.1109/ECTI-CON51831.2021.9454857.

[23]Z. Jianxin and W. Junyong, "Local occluded face recognition based on HOG-LBP and sparse representation," 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), Dalian, China, 2020, pp. 808-813, doi: 10.1109/ICAICA50127.2020.9182556.

[24]C. Agarwal, C. Bhatnagar and A. Mishra, "Evaluation of Image Inpainting Methods for Face Reconstruction of Masked Faces," 2023 International Conference on Electrical, Communication and Computer Engineering (ICECCE), Dubai, United Arab Emirates, 2023, pp. 1-6, doi: 10.1109/ICECCE61019.2023.10442807.

[25]L. Fangmin, C. Ke and L. Xinhua, "3D Face Reconstruction Based on Convolutional Neural Network," 2017 10th International Conference on Intelligent Computation Technology and Automation (ICICTA), Changsha, China, 2017, pp. 71-74, doi: 10.1109/ICICTA.2017.23.