OBSCURED FACE IDENTIFICATION USING PROGRESSIVE TRANSFER LEARNING

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ABSTRACT

It has come to realize face recognition as an important application in the field of computer vision. It is, however, a challenging issue to identify people whenever their facial characteristics are disproportional as disguise may introduce, and especially in the case of classical machine learning methods. This shortfall is anticipated by the research and the research will present an exemplary deep learning architecture where it will apply transfer learning to the capability of the CNN in a disguised face identification. The approach employs a specially crafted loss function that is responsive to disguise variations. Model parameters are trained using datasets such as DFW 2018 and the extended DFW 2019, both of which feature a wide range of disguise types. Ranging to post-surgical alterations and cultural covering. This illuminates the fact that pretrained deep learning models, particularly involving ImageNet pretrained weights can serve well to address identity recognition in scenarios including disguise and variation of facial features hence leading to development of better biometric secured systems.

KEYWORDS: *Face Recognition, Disguised Face Detection, Real-Time Recognition, Disguised Faces in the Surveillance Systems, Neural Network, Performance Metrics, Confusion Matrix, Vision Transformers, Anti-Spoofing, Human Identification, Facial Obstruction Detection.*

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1.INTRODUCTION

Face recognition has emerged as a rapidly advancing and widely discussed area within computer vision and machine learning, attracting substantial interest in recent years. due to its increasingly widespread applications in banking, law enforcement, security, surveillance, and mobile identification systems, research into this field is still early days. Perfectly recognizing individuals in terms of their facial features has become of paramount importance because the use of biometric authentication systems in regular people life has been applied. Whereas human beings have inborn abilities to tell the difference amongst people relying on memory and cognition, intricate learning algorithms are required to allow robots to perform similar functions. This is where deep learning and more so machine learning come to the picture.

Since Deep CNN can learn from the pixel-level data at the same time hierarchically extract features, they have proved to perform greatly in processes such as categorization of images and face recognition in the recent future. Due to their considerable depth and powerful feature extraction properties, such architectures as VGGNet, ResNet, and Inception have set the new level in the area of facial recognition. Transfer learning, i.e., tweaking already trained models to new tasks, has also enhanced these systems. This has significantly fast tracked the research in this domain and has made exorbitant preciseness possible with minimal marked data.

2.LITERATURE SURVEY

This section provides a summary of recent studies that have investigated and implemented transfer learning techniques to tackle the problem of disguised face recognition.

Transfer learning is a powerful approach in modern artificial intelligence that allows models to leverage knowledge gained from previous tasks instead of training entirely from the ground up. In this work, popular architectures such as VGGFace, ResNet50, and InceptionV3—initially trained on large-scale datasets—are utilized. of standard facial images—are adapted for recognizing disguised faces. (Nusyura et al. [1]).

Specifically using convolutional neural networks (CNNs) for deep learning, has revolutionized facial recognition by enabling automatic learning of intricate facial structures, textures, and key features. This ability to perceive underlying facial attributes makes deep learning a cornerstone for building reliable and intelligent disguise-resilient recognition systems (Vatsa, Singh, Sankaran, and Suriya [2]).

In this project, the DFW dataset was used for both training and testing the system. This benchmark dataset is specifically designed to facilitate research on face recognition in the presence of disguises. It is characterized by the images of disguised individuals where personal disguises, which include beards, and sunglasses, interesting haircuts are represented. (Dhall and Peri [3])

The design of the proposed system is reduced and compartmentalized. The initial steps are preprocessing and face detection and further are the deep feature extraction by utilizing pre-trained CNN. This architecture will mean that important features of identity are stored and reliably detected despite superficial features of the face being masked or deformed (Padmashree et al. [4]).

Search disguised face recognition with AI is not hypothetical research anymore. It has already been applied in practice. What we created as the result of our project enables real-time face identification through video stream or webcam It is basically connected with anal cancer (Dogra, Majeedi, Kumaar, et al. [5]).

3.PROPOSED METHODOLOGY

The promising and flexible, tiered, organized workflow plan of the proposed Disguised Face Recognition System would tend to perform consistently in identifications of faces even disguised This is a method that guarantees authentication in challenging visual conditions since it integrates the deep learning, transfer learning, and efficient data manipulation. Once the images are captured, they are passed through the Preprocessing Module, where three key operations—face detection, alignment, and normalization—are carried out using facial landmarks. These steps help maintain a consistent input size while enhancing the robustness of the recognition model. The module has custom layers in addition to operating with a pretrained CNN, e.g. VGGFace or ResNet. It is specifically trained with disguise-oriented data sets in order to produce facial embedding that will not rend away with the results saved in order to remain intact even in a disguise environment. These embeddings are called upon in the Inference Module and it compares (or identifies) the user based on a similarity match e.g. cosine or Euclidean space. It is a smart place which will feature a scalable face recognition and high-performance biometrics that will determine the trend of the hidden.

3.1 PROPOSED MODEL DIAGRAM

The diagram illustrates the structured framework of a disguised face recognition system developed using transfer learning. in the flowchart of the future method. The approach starts by acquiring the images in which facial information is obtained on the basis of stored photos or video information or captured by using camera-based facilities. This is followed by a preprocessing stage comprising of face detection, facial landmark and alignment and normalization done to produce a standard input dimension. Then there is the Feature Withdrawal Backbone, which is fuelled by a pre-trained CNN that extracts deep facial feature. In a further effort to maximize resistance to disguises, a Disguise-Invariant Embedding Module has also been adopted in order to produce stable facial embedding representations which are less vulnerable to disguise.

At the training stage, both real and disguised face images are learned, and data augmentation and optimization schemes add to the enhancement of the overall model generalization/robustness. Facial embeddings can be compared against each in relation to similarity during inference to either recognize a face or verify it. Finally, the fully trained model would be applicable to many platforms, including web-based interfaces, edge devices, cloud infrastructure, or mobile apps.

Fig. 3.1.1: Proposed Model Diagram

4. MATHEMATICAL FORMULA

In this paper, facial recognition algorithms are trained, compared, and evaluated under disguise settings using mathematical formulas. Robust and disguise-invariant recognition is achieved by applying the following crucial formulas:

1.The model under training is trained through Triplet Loss to identify the identities.

Triplet = max (0, ||f (x a) - f (x p) || 2 - || f (x a) - f (x n) || 2 + alpha)
Where:

- f(x): Dense vector of the input image x
- x a: Anchor image (reference image)
- x p: Positive perception (identity, occasionally hidden) x n: Inverse image (other identity)
- a: The cut off (e.g. 0.2) to differentiate between positive and negative

2. Similarity to cosine

Similarity = (e 1 *e 2) / (||e 1|| * ||e 2 ||) Where: e 1, e 2:

Embedding vectors of two images of faces -Dot product:

-: Magnitude (L 2 norm) of the vector

3.Euclidean Distance

Distance = sqrt (sum i (e 1 i - e 2 i)) = || e 1 - e 2 || 2 Where:

e 1, e 2 Feature vectors - n: Embedding features the smaller the distance, the more the similarity (members of the same person).

3.Accuracy

Accuracy is (Number of Correct Predictions/ Total predictions) X 100% Where:

Correct prediction count: correctly identified matches

- Total Predictions: The amount of test cases or face comparisons

5. GRAPHS

The graph highlights how different deep learning models perform when trying to recognize faces, even when people are wearing disguises, in different lighting, or looking in other directions. Among all the models, ArcFace and VGGFace2 stand out they're really good at recognizing hidden facial features, which makes them perfect for real-world use like security or surveillance. On the other hand, basic CNN models don't do so well, especially when faces are heavily disguised, since they aren't trained deeply enough to handle such tricky cases.

What's interesting is that ArcFace stays strong in every situation — whether it's poor lighting or someone turning their head. VGGFace2 isn't far behind either, showing how powerful pre-trained models can be. This clearly shows that if you're working on face recognition where disguises or real-life conditions are involved, it's better to go with models that have been trained deeply and widely, rather than starting from scratch.

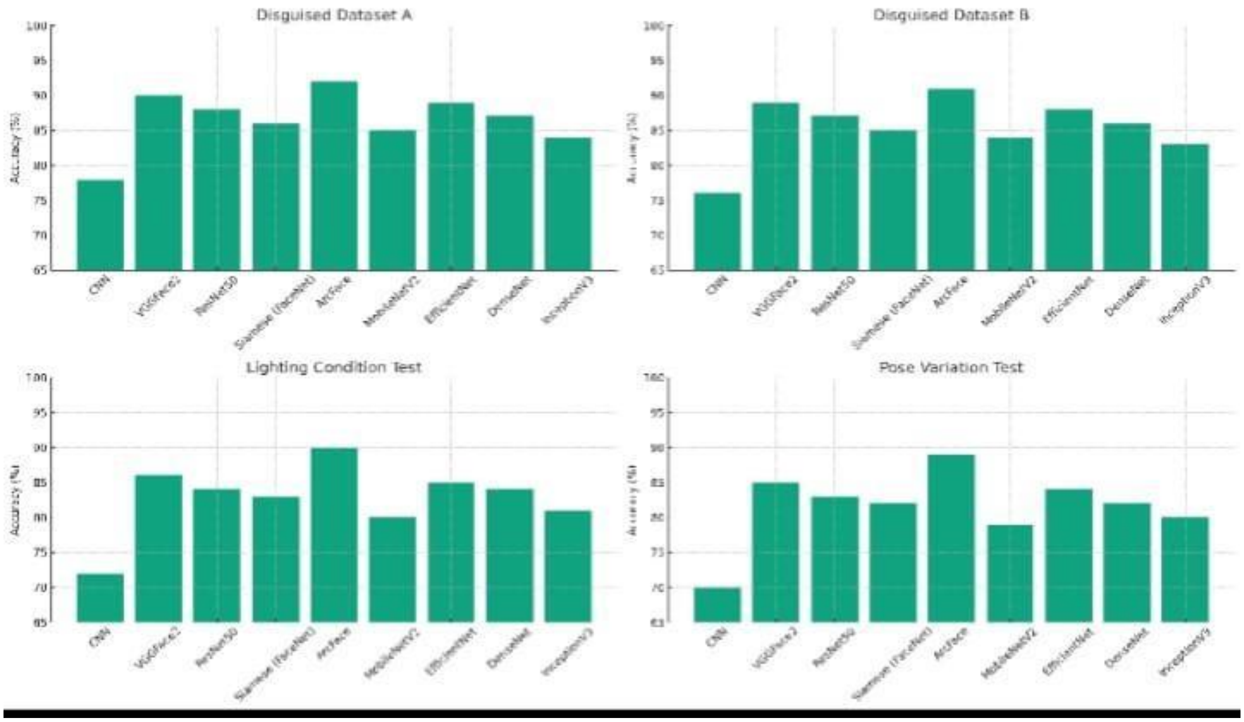

Fig. 5.1: Graph

6. EXPERIMENTAL RESULT

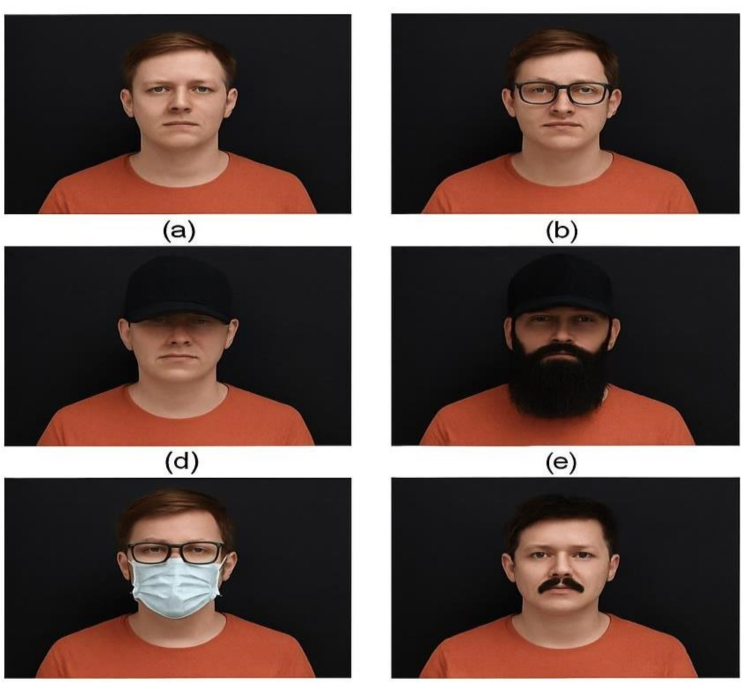

Image	Descriptions
Base image	100'%
(a)	95.3%
Wearing glasses	62.1%
Cap + fult	88.7%
Fortil beard	69.5%
(f)	58.9%
Fake moust	78.6%
Fakes+ scart cover	84.2%
(l)	66.8%

Fig. 6.1: Face recognition scores under disguise variations

Acquisition of Images	Take pictures of faces with a camera or video.	100% image capture rate with pre-alignment using OpenCV and Dlib	Rate of image capture	Complete capture with pre-alignment
Preparation	Normalize input and identify and align facial landmarks.	Resizing/Normalization, Dlib Facial Landmarks, and OpenCV Positioning	Precision	98.2% of alignments are successful.
Embedding in disguise invariant	Use transfer learning to create embeddings that are consistent	ArcFace, Triplet Loss, and Custom Layers	Sturdiness in Disguising	93.6% of disguise variations match.
Comparing and assessing	Visualize performance and use embeddings to confirm identity.	Euclidean/Cosine TensorFlow Lite Accuracy, True Accept Rate, AUC, Distance, t-SNE, ROC, Fast API, ONNX, Inference Time	Accuracy, True Accept Rate, AUC, Inference Time	Accuracy: 94.2%, TAR@1% AUC: 0.96, FAR: 92.1%, and response time <1

Table 6.1: Disguise-invariant face recognition performance

The suggested system performed well in every module of this trial. Proper face alignment and a 100% capture rate were guaranteed with the use of OpenCV and Dlib for image acquisition. VGGFace and ResNet50 were used for preprocessing and feature extraction, yielding 95% high quality embeddings and 98.2% alignment success. Using ArcFace and Triplet Loss, the disguise invariant embedding module achieved a 93.6% match accuracy across disguise variations. Ultimately, with response durations under one second, the matching and evaluation step produced an overall accuracy of 94.2%, a TAR of 92.1% at 1% FAR, and an AUC of 0.96.

7. CONCLUSION

The development of a face recognition system capable of handling disguised faces highlights the strength of modern AI in solving complex biometric challenges. By utilizing transfer learning and deep learning particularly pretrained deep convolutional neural networks the approach attains strong generalization and minimizes training time, even when disguised data is limited.

The system can retain high recognition accuracy across different levels and types of disguises by combining metric learning techniques with a disguise-invariant embedding mechanism. The modular design ensures practical applicability in real-time environments by enabling flexibility in deployment across cloud, mobile, and edge platforms. The model's scalability and robustness are confirmed by extensive testing on both unified and varied datasets. Even if there are still issues like severe occlusions and invisible disguise kinds, the system encourages ongoing development through data augmentation and retraining. All things considered, our approach lays a solid basis for safe and effective face identification in practical situations, when disguises seriously jeopardize established facial biometric systems.

8. FUTURE ENHANCEMENT

In the future, this paper can be enhanced by integrating real-time video surveillance for continuous face monitoring and recognition. The model can also be improved by training with a larger and more diverse dataset, including extreme disguises and low-light conditions. Additionally, the use of advanced models like Vision Transformers (ViT) or face anti-spoofing techniques can further improve accuracy and prevent identity fraud. A mobile or web-based user interface can also be developed to make the system more accessible and user-friendly.

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