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DISGUISED FACIAL RECOGNITION USING NEURAL NETWORKS - A SURVEY

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Abstract — **Face recognition software is being used more often in a wide range of applications, but worries about privacy and exploitation have sparked interest in creating methods for "disguised" face identification. The use of neural networks for disguised face identification has recently attracted the attention of academics, who trained their algorithms on pictures of people with masks, hats, and other facial coverings. Yet, there are a number of difficulties in creating efficient disguised facial recognition systems, such as a lack of training data and the requirement to take different lighting and position changes into consideration. The use of adversarial networks, infrared imaging, and deep learning techniques are among the latest advancements in the field of masked facial recognition using neural networks that are examined in this review. The study also covers prospective uses for concealed face recognition technology as well as the moral issues surrounding its implementation. The survey's findings show that neural networks may be used to mask face recognition in order to satisfy privacy concerns while still enabling accurate identification of people in a range of scenarios.**

Keywords — Disguised Facial Recognition, Neural Networks, Machine Learning, Deep Learning, Adversarial Networks.

1. 1. INTRODUCTION

Facial recognition technology has become a ubiquitous tool for identifying individuals in a wide range of applications, from security systems to social media platforms. However, as the use of this technology has increased, so have concerns about privacy and the potential for misuse. One approach to addressing these concerns is to develop techniques for "disguised" facial recognition, which can identify individuals even when they are wearing masks, hats, or other facial coverings.

Researchers have been investigating the use of neural networks for masked face recognition in recent years. Neural networks are a form of machine learning algorithm that can be trained to identify patterns in huge datasets. They are designed after the structure of the human brain. By training neural networks on images of individuals wearing different types of disguises, researchers hope to develop algorithms that can identify individuals even when their faces are partially covered.

There are several challenges associated with developing effective disguised facial recognition systems using neural networks. One key challenge is the limited availability of training data. It can be challenging to obtain enough photos to train a neural network to detect face coverings because they are rather uncommon in many datasets. This is especially true for masks, which have proliferated since the COVID-19 epidemic and are now used considerably more often.

The necessity to create algorithms that can withstand changes in lighting, position, and other aspects that might impact how a face looks is another difficulty. It can be challenging to generalise neural network performance to new datasets or real-world contexts since neural networks are very sensitive to the unique patterns they are trained on.

Despite these difficulties, the area of hidden facial recognition using neural networks has seen a number of encouraging advancements. Researchers have explored a range of techniques for training neural networks on disguised faces, including using adversarial networks to generate synthetic images that simulate the appearance of facial coverings.

One promising approach is to use a combination of visible and thermal imaging to identify individuals. Because thermal imaging is less affected by facial coverings and lighting conditions, it can provide a complementary source of information to visible imagery. By combining these two modalities, researchers have been able to develop algorithms that can identify individuals with a high degree of accuracy even when they are wearing masks or other facial coverings.

Another approach is to use deep learning techniques to extract features from facial images that are invariant to variations in lighting, pose, and other factors. By using these invariant features to train a neural network, researchers hope to develop algorithms that are more robust to real-world variations in appearance.

In conclusion, disguised facial recognition using neural networks is an area of active research that holds promise for addressing some of the privacy concerns associated with facial recognition technology. While there are significant challenges associated with developing effective algorithms, researchers are exploring a range of techniques for training neural networks on disguised faces, including using adversarial networks, thermal imaging, and deep learning approaches. As the use of facial coverings becomes more common in everyday life, disguised facial recognition may become an increasingly important tool for identifying individuals in a range of applications.

2. 2. Background and Related Work

This study [1] compares the performance of a deep learning framework for covert facial recognition to that of cutting-edge techniques. Amarjot Singh and his coworkers (2017) investigated veiled face detection utilising facial key points using a spatial fusion convolutional network. The challenge of facial recognition is significant and difficult. In this paper, a methodology for facial key point detection for veiled face detection is introduced. A simple background face masking (FG) data set employing veiled face identification (DFI) frames and a sophisticated background face masking (FG) data set were the two datasets that were the subject of the studies that were described. The provided dataset's abundance of obscured pictures enhances deep learning network training and eliminates the requirement for transfer learning. The orientations between linked points in a star network topology are used in the proposed classification framework to identify faces. 1000 training photos randomly chosen among shrouded faces, 500 validation images, and 500 test images are used to train a spatial fusion CNN. Shin and her coworkers contrast the masked face with five indistinguishable masked faces, one of which has a masked face. For data sets with simple and complicated backdrop face masks, the classification accuracy is 85% and 56%, respectively.

To build a face recognition system with a limited amount of training data, researchers [2] suggested a new deep neural network training approach. In this paper, we present a single-sample face recognition system based on sample augmentation in feature space and transfer learning. A deep convolutional neural network model is pre-trained using a common multi-sample dataset to extract compact face characteristics. A k-class feature transfer approach is suggested to increase the within-class variance of gallery features by extending the samples in the feature space. A deep convolutional neural network model is pre-trained on a multisample common data set to extract compact face characteristics. Nine test photos and one training image from each person were used in the experiments. The remaining 360 of his photographs are utilised as test samples, while the 40 training samples are made up of each individual's normal image. Enhance recognition performance effectively.

The non-intrusive nature of picture gathering in facial biometrics promotes face recognition in the majority of biometrics identification, according to studies conducted at the Norwegian Biometrics Laboratory under the direction of Narayan Vetrekar (2020) [3]. They have shown how to use the system's functionality. This article investigates spectral imaging's potential for facial identification. Modern techniques are used to both combined and individual spectral bands, and the outcomes are compared with the suggested method. The presence of face recognition software in FRS makes it very easy to wear disguise-enhancing accessories like long beards, caps, or haircuts. The focus of this research was on identifying face pictures with short-term occlusion of facial areas utilising disguised variations like short and regular beards. To emphasise the significance of the suggested strategy, they presented their experimental findings in terms of validation rate and got Equal Error Rate (EER), Genuine Match Rate (GMR) @ 5%, and 10-lse Match Rate (FMR). Proven. The findings showed how crucial the suggested strategy is for learning spectral band characteristics effectively for reliable performance when compared to cutting-edge occluded face identification techniques.

A study team from the Omkar Indian Institute of Science in Bengaluru, led by Saumya Kumaar [4], described obscured facial recognition using neural networks in 2019. One of the most extensively studied subjects in history is face recognition, or what is more popularly known as facial recognition. The group proposes an experimental approach for the veiled face identification challenge that classifies input data using convolutional neural networks and conventional neural network architectures. Singh et alinitial .'s suggestion for facial keypoint-based verification of veiled faces was made in 2017. When they suggested utilising an existing spatial fusion convolutional network design, it was used. When applied to practical issues like intruder detection, the architecture thusly shown is intended to be user-friendly. For both the keypoint prediction model and the face classification model, they employed CNN. The classification results are 86.6% and 72.4%, respectively, for the data sets with simple and complicated backdrop face masks. Several algorithms are used to initially discover faces, and the classification approach is then only used for the faces that have been found, not for the full image. By removing unnecessary portions of the image, this technique reduces processing time.

Jiankang Zafeririou (2020) [5] reports that the best approach for face identification is face representation utilising deep convolutional neural network embedding in "ArcFace for Disguised Face Recognition". The majority of face recognition technologies are susceptible to impersonation and spoofing. The technical specifics of the DFW2019 challenge entry are explained by Zafeririou. Current facial recognition systems have significant difficulties as a result of spoofing, which results in high mutual likeness and obfuscation, which causes internal dispersion. These three protocols are face verification protocols that ask face recognition algorithms to determine if a pair of face photos are authentic or not. The suggested intraloss lowers the true acceptance rate (GAR) to 56.80%, the inside acceptance rate (FAR) to 0.01 and the true acceptance rate (GAR) to 17.60%. At 1e-4 FAR, intra-loss increases GAR from 91.43% to 94.48% while inter-loss raises GAR to 97.99%. The combination of these two losses, which complement one another, raises the GAR to 98.43% at 1e-4. Modern performance is provided by this solution for the DFW2019 challenge.

A group led by Arulkumar Subramaniam, Indian Institute of Technology, Madras (2020) [6], "Feature Ensemble Networks with Re-Ranking for Identifying Disguised Faces in the Field," identifies face recognition as an essential and demanding biometrics-oriented computational technique, said that the assignment involved matching up faces to persons visually. Face-recognition algorithms now perform better than humans on several benchmark datasets because of the development of deep learning. They began by utilising two newly suggested loss functions to improve a base model that had already been trained. They suggested a transfer learning-based ensemble model for veiled face detection. To solve the issue of finding concealed faces in the field, they suggest a Feature Ensemble Network, which is an amalgamation of many cutting-edge face recognition networks. The group examines the use of re-ranking techniques in covert face recognition applications. It is particularly challenging to identify real face photographs from false ones because of the inherent ambiguity of 2D facial images. As they identify between photographs of various identities, concealment and plastic surgery processes are rather straightforward. They used a little-used tactic of moving face recognition to a covert face recognition task, and via extensive empirical investigations, they were able to demonstrate that it considerably increased performance.

Unsupervised domain matching for covert face recognition was researched by Fangyu Wu and colleagues (2019) [7]. There are several applications for facial recognition (FR). A lot of attention has been paid to identity verification, public safety, and surveillance. When detecting the same obscure-looking item while the accuracy declines dramatically, current FR systems have a difficult time. A Domain Style Adaptation SubNet (DSN) and an Attention Learning SubNet (ALN), which together yield domain recognition data and obfuscated faces, make up the proposed unsupervised domain adaptation model (UDAM). They put out a methodology to deal with the challenging issue of face recognition with domain bias. To show the efficiency of the suggested strategy in adjusting to the domain shift problem, tests were done utilising Simple and Complex FGD and ID V1 databases. Performance is greatly improved by the suggested models, with gains ranging from 6% to 15.5%. This demonstrates that the suggested strategy is effective even in the presence of sparse and unlabeled data in the target domain. For issues involving unsupervised domain matching, this is a typical occurrence.

Using deep transfer learning and noise-based data augmentation, a research team from the Department of Electrical Engineering led by Muhammad Khan (2021) [8] proposed an automated efficient convolutional architecture for disguise-invariant face identification. Typically, face recognition is categorised as a biometric technique that uses a person's distinctive facial traits to identify them. The challenge of identifying faces when their facial features have been intentionally or accidentally altered is known as disguise invariant face recognition or DIFR. This work's key contribution is to employ the already available detection and classification approaches, compare them, and choose the best ones. They claim that Apple's Face ID, which employs infrared cameras, conventional cameras, and floodlights to collect face photos, is the driving force behind these upcoming milestones. The suggested system does not function in all illumination circumstances, particularly darkness, because the pictures in the training dataset are only colour photos. The efficacy of the suggested approach is demonstrated by Disguised Faces in the Wild (DFW), IIIT Delhi Disguise Version 1 Face Data Set (ID V1), Polytechnic University Disguise and Make-Up Faces (PolyU), Makeup Induced Face Spoofing (MIFS), YouTube Makeup (YMU), and Virtual make-up (VMU). A thorough comparison with various cutting-edge DIFR (Dismasks Invariant Facial Recognition) models serves to further confirm our investigation. The average accuracy of the suggested technique was 98.19%, and its average execution time was 0.32 seconds, outperforming comparable models.

The Department of Computer Science (2020) [9] and a team led by Anshuman Suri of Suri suggested the A2-LINK method as a model incorporating the ideas of active learning, domain matching, and hybrid noise enhancement. reports that she trains The quantity of labelled data with variables that is available restricts its ability to perform at almost state-of-the-art levels. According to experimental findings, the algorithm significantly enhances the model when it is being tuned. Modern face recognition programmes do almost as well as humans do on confined and semi-constrained datasets. Rich variables like disguise, cosmetics, and low resolution are absent from these records. A2-LINK effectively selects unlabeled data points from the target domain for labelling by using passive input from the model itself. By handling both disguise and multiresolution as covariates, the proposed technique and its earlier iterations produce comparatively good performance increases. A2-LINK significantly improves model refinement for all procedures on the Disguised Faces in the Wild (DFW) and Disguised Faces in the Wild 2019 (DFW2019) datasets, according to experimental results. The suggested algorithmic framework exhibits strong generalisation on a variety of variables as well as functionalized models (L-CSSE, Densenet, ArcFace). The average classification rates for the DFW dataset's 0.1% and 0.01% are 95.96% and 92.00%, respectively.

Using concealed face recognition, a research team from Chang Winston Hsu National Taiwan University led by Kaipeng Zhang (2018) [10] suggested a two-step training method for DCNN. In the Disguised Faces in the Wild benchmark, the suggested solution outperforms contemporary conventional face detection techniques. One of the most active subfields in computer vision is facial recognition (FR). Deep convolutional neural networks (DCNN) are used by researchers to identify faces. It includes two of his DCNNs for identifying faces commonly and a chosen transformation matrix for fitting faces that are concealed. To obtain the transformation matrix for obfuscated face recognition fitting, we first train two DCNNs for generic face recognition. The identification features derived from the DCNN are projected onto the PCA subspace defined by the main component of the maximum sample variance of the DFW training set during the adaptive training phase. The DFW dataset's 1% and

0.1% classification values are 86.41% and 72.21%, respectively.

In ‘Benchmarking deep learning techniques for face recognition’, Qiangchang Guo (2019) [11] reported that recent progress in deep CNNs has substantially improved state-of-the-art performance in face recognition. With the availability of large datasets, researchers have developed a number of CNN models. In the VGG16-BN model, Batch Normalization (BN) layers are added before ReLU, which can accelerate network training. Centre loss is proposed to reduce intra-class variations. Cyi is the ytih class centre of deep features. The research involved 5 test datasets with different characteristics and four popular training datasets. The researchers compare the accuracy of different Convolutional Neural Networks models within the same deep learning framework. Results show that the PyTorch-based models tend to obtain the best performance among these three frameworks. When the number of Graphical Processing Units increases to 4, Caffe, TensorFlow and PyTorch have 101%, 68% and 86% improvement.

In this paper [12], the objective is to face recognition is to identify the label of a given class. Face recognition can be used as a part of many interesting and useful applications like authentication, criminal detection, Human-computer interface applications, and many more similar applications. The objective of face recognition is to identify the class to which a human face belongs. In the traditional face recognition systems hand crafted features like gist, Hog and LBP are used. They propose to use deep convolutional features to better represent the given facial image. In this study, they suggested using deep CNN-based features to the challenge of face recognition. They also examined in this study how well various Deep CNN models perform the job of facial recognition. First, face characteristics are taken from CNN models that have been previously trained, such as VGG16, VGG19, ResNet50, and Inception V3. The classification job is then carried out using a deep neural network. The experimental investigations make use of the ORL dataset to demonstrate the efficiency of the suggested paradigm.

In this paper [13], Experiments carried out on the Disguised Faces in the Wild dataset are discussed. DFW dataset is collected from the Image Analysis and Biometrics Lab from IIIT Delhi which consists of 1000 subjects with a total of 1,11,157 images. 400 samples are used for training and 600 samples are used for testing. Confidence levels are the likelihood of the results being true for the total population and expressed in percentage form. It is one of the measures used in the proposed system to recognize partially occluded faces. Out of 1000 samples, 930 samples were correctly recognized and 70 samples were incorrectly recognized. Experimental results demonstrated that the proposed system provides a confidence level of 93% and it outperforms the state of art with other existing partially occluded face recognition algorithms.

An innovative technique for detecting and recognising persons who conceal their identity by concealing their faces with scarves has been put forward in this study [14]. After extracting face features using a pre-trained Convolutional Neural Network (Alex-Net Model), the classification job is carried out using a multi-class Support Vector Machine (SVM) technique. Additionally, a fresh dataset of covered faces has been included for the deep network's training. For police enforcement and other groups, this is very helpful because it makes it easier to find criminals, Protestants, or anybody else who covers their identity. The Viola-Jones detection technique is used to detect faces. The CNN (Alex-Net) is fed with the identified and previously processed facial picture as input. A high accuracy rate is attained when the suggested technique is evaluated on a recently introduced disguise dataset. By adding more photos to the dataset or employing a convolutional neural network with a much deeper learning layer, accuracy may be further increased.

In this research paper [15], they offered a DCNN-based method for identifying impostors and distinguishing persons in disguise. On a sizable dataset made up of still photos and video frames with L2-softmax loss, we train two distinct networks. They combined the two networks' respective feature sets and demonstrate that the combined characteristics are useful for distinguishing between imposters and disguised faces in the field. They constructed an ensemble of two deep CNNs and get excellent early results. Future approaches to this issue may be constructed using the components of their strategy. The models are trained on a sizable quantity of data, and the DFW challenge test set serves as our reporting platform for outcomes.

3. Literature Review

Related Studies	Advantages	Disadvantages	Methodology
[1]	1. With the use of 14 facial essential points, a disguised face may be recognised. 2. Used two datasets of an annotated face key points that are used to train deep learning architectures.	1. High computational complexity 2. Limited interpretability	Spatial Fusion CNN
[2]	1. A deep CNN model is pre-trained using a standard multi-sample data set. 2. The feature space is expanded using the KCFT method, which enhances the intra-class variances of gallery characteristics.	Transfer learning with Inception-Resnet-V1 can sometimes suffer from overfitting.	Transfer Learning, CNN - Inception-Resnet-V1
[3]	1. Introduced an innovative approach that first extracts the histogram properties across several bands using the HOG method. 2. The set of histogram features is then trained in an affine feature space to provide discriminative features.	1. HOG features are sensitive to the quality of the input image. 2. HOG features are based on local image gradients and may not be able to capture fine details in the image.	Affine Hull Feature Space, Histogram of Oriented Gradient Features
[4]	This approach saves time by avoiding the unnecessary (non-face) portions of the picture.	The model is sensitive to the input image's quality and may be impacted by things like noise, blur, and changes in lighting.	Key-Point Prediction Model, Face Classification Model - CNN
[5]	The RetinaFace for face detection and alignment and the ArcFace for face feature embedding were used to achieve cutting-edge performance on the DFW2019 challenge.	When faces are partially obscured by accessories like glasses, hats, or scarves, RetinaFace has trouble detecting them.	Face Detection and Alignment by RetinaFace Face Feature Embedding by ArcFace
[6]	FEBNet is designed to efficiently extract informative features from input images, which can be useful for downstream machine learning tasks.	FEBNet is a complex model that requires a significant amount of computation and memory resources, which can be a challenge for some applications.	Feature EnsemBle Network (FEBNet)
[7]	To create images with translated styles, the DSN contains unsupervised cross-domain adversarial training.	The Baseline Deep DFR Model may be sensitive to the quality of the input image.	Baseline Deep DFR Model, Transfer Learning, CNN - ResNet-50

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[8]	Extracts discriminative and robust features in the presence of many disguise changes.	ResNet-18 and ResNet-50 are prone to overfitting if not properly regularized.	Viola Jones, CNN - ResNet-18, ResNet-50, Inception-V3 & SqueezeNet
[9]	The proposed A2-LINK method combines active learning, domain adaptability, and hybrid noise augmentation principles to train models to attain close to state-of-the-art performance.	A2-LINK is a relatively new face recognition model, and its performance has not been extensively evaluated or compared to other models.	Local Class Sparsity Supervised Autoencoder (L-CSSE), ArcFace, DenseNet, A2-LINK
[10]	They discovered that, in comparison to one-stage training, two-stage training can enhance performance.	PCA considers the most relevant features of the data and assumes that the data is normally distributed and linearly correlated, which may not always be the case.	DCNNs, PCA
[11]	Center-loss, SphereFace, CosFace, ArcFace, GoogLeNet, Inception-v3 and ResNet-50 models achieve better performances.	Computational cost is high with respect to model training.	AlexNet-v2, VGG-16, VGG-16-BN, ResNet-50, Inception-v3, and DenseNet-121
[12]	More discriminative features are extracted and hence the generalization ability is good. The performance of ResNet based model is better when compared to the other models.	ResNet50's performance can be sensitive to hyperparameters, such as learning rate, batch size, and regularization strength. Finding the optimal hyperparameters can be time-consuming and computationally expensive.	VGG16, VGG19, ResNet50 and Inception V3
[13]	The partially obscured face pictures in the proposed system are fed into CNN for training, which automatically learns the input images using filters to lessen the learning cost. It consistently records the spatial elements needed to effectively discern partly obscured face photos.	CNN with face encodings can achieve high accuracy in face recognition, it is still prone to errors, particularly when dealing with variations in lighting, facial expressions, or occlusions. It recognizes a limited number of faces, making it unsuitable for applications that require large-scale recognition	CNN with Face Encodings
[14]	The accuracy is really compelling, and it demonstrates that the algorithm does a good job of identifying faces that are hidden by scarves.	A deeper convolutional network and more photos in the database can both help the system become even better. However, when the eye area is also covered up, it is still difficult to identify and recognise these disguised pictures.	AlexNet and Multiclass SVM

[15]	The approach yields a 92% true accept rate (TAR) at a 0.0001 false accept rate (FAR) and a 96.4% TAR with a 0.001 FAR. This demonstrates how well the proposed technique can identify persons using makeup and disguises.	ResNet-101 and Inception-ResNet-V2 are very deep neural networks which makes them computationally expensive to train and deploy.	ResNet-101, Inception-ResNet-V2

Table 1 Relevant studies on advantages and disadvantages of approaches to identify disguised facial recognition

4. Conclusion

In conclusion, the study of hidden facial recognition using neural networks is a topic of study that is fast developing and has a wide range of potential and obstacles. Although there has been a lot of development in creating algorithms that can identify people wearing different forms of facial coverings, there are still a lot of challenges to be addressed. The lack of training data, especially for masks, which have become considerably more prevalent in the aftermath of the COVID-19 outbreak, is one of the main problems.

Despite these difficulties, the discipline has seen a number of encouraging advancements, including the use of adversarial networks, thermal imaging, and deep learning techniques. Combining visual and thermal imaging to identify people is one of the most promising methods because it can give supplementary information that is less impacted by face coverings and lighting conditions.

While there is still much to be done to create good disguised face recognition systems using neural networks, this technology has a lot of potential for overcoming some of the privacy issues with facial recognition. In order to produce a more safe and more privacy-friendly method of facial recognition that can be applied in a variety of applications, researchers are working on algorithms that can recognise people even while they are hiding their faces with masks, hats, or other facial coverings.

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