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REVIEW ON FACE LIVE LINESS AUTHENTICATION

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Abstract— **Today, as the society is developing rapidly the network and information technologies have caused rapid change in the traditional business activities. Online transaction are rapidly developing based on the technologies used on mobile, tablets and PC along with use of Internet of things. With use of such technologies, online treats to business transaction has increased tremendously. Thus, different bio- Factors like face recognition eye retinas, fingerprints, etc are integrated in the existing online system to make them more secure. Face recognition with liveliness authentication is one such method which will help to increase the safety in transactions especially in online banking. This paper gives the review of face recognition system with liveliness detection that can be used for secure online transaction.**

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I. INTRODUCTION

Due to the daily addition of new features, mobile and internet banking has emerged as one of the most significant technological advancements. Most financial companies offer online banking application to their customers. Thus security and customer privacy has become an utmost .Priority for the companies . Online banking frauds carried out using fake face ,id's , etc. has become serious threats . In order to neutralize this threats, biometric feature like face recognition can prove to be viable option in online banking. Face recognition and face liveliness authentication can be integrated in online banking system to make transaction more secure. The use of face recognition system has seen an upward trend for secure online transaction however there are few flaws in this system that could be exploited using spoofing ,twining , etc. In order to make this system completely secure face liveliness detection along with face recognition can prove to be more effective.

II. REVIEW OF LITERATURE

[1] Boris Knyazev proposed leveraging massive facial recognition data for emotion categorization. The author offers a solution to the problem of emotion recognition in this paper. The author suggested a model that extracts spatial and acoustic information from videos. Convolutional neural networks, which were pre-trained on big face recognition datasets, are used to capture spatial characteristics. The author demonstrates how using robust, commercially available face recognition networks improves the accuracy of emotion recognition. By using this, it can increase the performance on the test dataset from the previous year's highest score by roughly 1. This achieve a 60.03visual temporal information, putting it in the top 2 for this challenge.

[2]Ran He proposed the Wasserstein CNN and Learning Invariant Features for NIR-VIS Face Recognition. In order to match critical applications in the forensics, security, and commercial sectors with facial images obtained from various sensing modalities, heterogeneous face recognition (HFR) is used. The substantial intra-class variation among heterogeneous face photos and the scarcity of training sets of cross-modality face image pairs, however, make HFR's problems more complex than those of standard face recognition. This study suggests the Wasserstein convolutional neural network (WCNN) method for identifying features that are constant across near-infrared (NIR) and visible (VIS) facial images (i.e., NIR-VIS face recognition). The WCNN's low-level layers are trained using widely accessible VIS face images, while the high-level layer is split into three sections: the NIR layer, the VIS layer, and the NIR-VIS shared layer. The common NIR-VIS layer is intended to learn a modality-invariant feature subspace whereas the first two layers are focused on learning modality-specific features. In order to quantify the differences between diverse feature distributions, the Wasserstein distance is added into the NIR-VIS common layer. Invariant deep feature representations of heterogeneous face images employ W-CNN learning to minimize the Wasserstein distance between the NIR distribution and the VIS distribution. A correlation prior is added to the fully connected WCNN layers to condense the parameter space in order to prevent the over-fitting issue that arises with small-scale heterogeneous face data. A low-rank constraint in an end-to-end network implements this prerequisite while testing, and an effective computation for diverse data during training.

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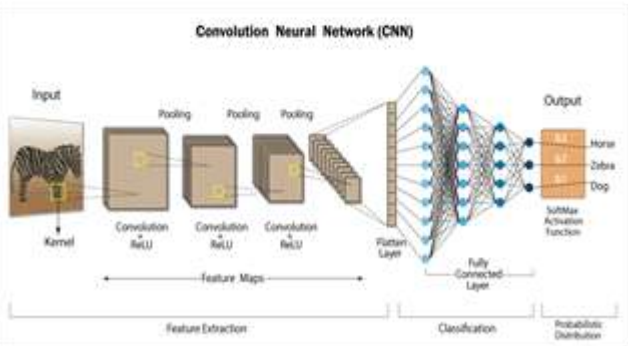
Comprehensive tests on three difficult NIR-VIS face recognition databases show that the WCNN method outperforms state-of-the-art methods.

[3]Yuxiang Zhou and Hongjun Ni proposed that Face and Gender Recognition System Based on Convolutional Neural networks. This paper proposes a Face and Gender Recognition System that makes use of convolutional neural networks (CNN). There are two parts to the system: a face recognition module and a gender recognition module. In order to extract face and gender attributes from a picture, both the face recognition module and the gender recognition module use pre-trained CNN. With regard to the face recognition module in particular, they train CNN using the public datasets Labelled Faces in the Wild (LFW), YouTube Face (YTF), and VGGFace2 to increase the precision. Using the public dataset , they train CNN in the gender recognition module to get the highest recognition accuracy possible.



[4]Ahmed El Sayed, et al proposed the Effect of Super Resolution on High Dimensional Features for Face Recognition in the wild. The majority of face recognition systems, according to the authors, use faces taken from uncontrolled, natural environments. The facial photos are frequently blurry or of low resolution due to the limitations of cameras. In order to increase the resolution of such photos, super resolution methods are essential, particularly when image enlargement is needed due to tiny image size. In this paper, one of the most cutting-edge algorithms for image super resolution will be used to show its effects. With the help of photos from the Labelled Faces in the Wild (LFW) dataset, numerous before and after 3D face alignment scenarios are applied to show how the method works. Unsupervised algorithms with high dimensional extracted features are used to test the resulting images on a closed set recognition process. In comparison to recently published findings derived from unsupervised algorithms on the same dataset, the inclusion of the super resolution approach led to a considerable improvement in the recognition rate.

[5]Momoko Hada, et al proposed that the transformation of an avatar face giving a favourable impression affect human recognition of the face. The author looked into how human face-recognition abilities are impacted by the various looks of 3D avatar faces. With the use of synthetic facial images, they carried out an encoding and testing experiment and intentionally changed the perceived impression intensity in three different dimensions. Also, they evaluated the favorability of the synthetic faces that were utilised as visual cues in face-recognition tests subjectively, and they discovered that facial alteration, which reduced the favorability impressions, often worsened human face recognition performance

[6]G. Kim et al proposed face liveness detection based on texture and frequency analyses. The basic purpose is to differentiate between live face and fake face (2-D paper masks) in terms of shape and detailedness. The authors main goal is to distinguish between a real face and an artificial face (2-D paper masks) in terms of shape and level of detail. For separating real faces from 2-D paper masks, the authors have presented a single image-based fake face detection technique based on frequency and texture studies. The power spectrum-based frequency analysis method used by the authors makes use of both the information present in the high frequency areas as well as the low frequency sections. Also, a description method based on Local Binary Pattern (LBP) has been put into practice for examining the textures on the provided facial photos. According to the authors, there are two benefits to using frequency information. The first is that there are different 3-D shapes, which causes different low frequency zones and is related to the lighting component produced by the overall shape of a face. Second, the disparity in the high frequency information results from the difference in detail information between the live faces and the masks. The texture information is obtained because, in comparison to photographs acquired from 3-D objects, images taken from 2-D objects—particularly the illumination components—tend to lose texture information. Frequency-based, texture-based, and fusion-based feature extraction methods are all now being used for feature extraction.

[7] Zeyd Boukhers, et.al proposed Blinking based analysis liveness detection. Considering long-range dependencies on the observation sequence, the authors modelled blinking behaviors using CRFs. Next they contrasted the CRF model with an HMM(hidden markov model)-like generative model and an Ada Boost-like discriminative model. As probabilistic models for segmenting and labelling sequence data, conditional random fields (CRFs) are primarily utilised in natural language processing because they can accommodate long-range dependencies on the observation sequence. The image sequence, which alternates between close-up and non-close-up states, serves as a representation of the blinking activity.

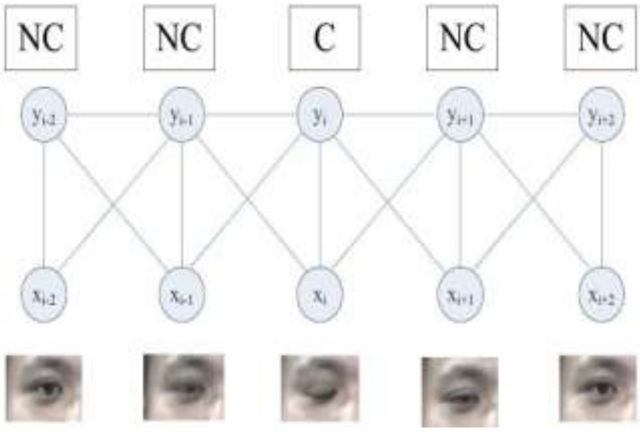


Fig 1Graphic structure of CRF-based blinking model. Here we show the model based on contexts of observation of size. Labels C and NC are for close state and non-close state respectively

CRFs are organized in a line chain by the authors. It has established data yt = 1, 2,..., c, t = 1...T, and observation xt in a discrete manner. The authors claim that the half-open state is challenging to define consistently across individuals since the size of the half-open state depends on the individual's eye appearance; for instance, the open state of a small eye may resemble the half-open state of a huge eye. Regarding the blinking model, the authors are using two state labels, C for close state and NC for non-close (including half-open and open), to label eye states. To test their method, the authors employed a video database with blinking video clips and imposter video clips. They used a total of 80 clips from the blinking video database for 20 persons, four clips per person: the first clip comprises video without glasses in frontal view, the second clip is with thin rim glasses in frontal view, and the third clip has video with black frame glasses in frontal view. Five-second video clips with a 30fp frame rate and a 320240 resolution are being used. The amount of blinks in each clip ranges from 1 to 6. The authors employed 180 picture imposter video clips of 20 people with various photo motions, such as rotating, folding, and moving, to evaluate the capabilities against photo forgers.

[8] Sanjay Ganorka et. al proposed Face Liveness Detection Using Machine Learning. To recognize the spoofing attack, the study suggests liveness detection. The implemented system primarily uses a KNN classifier and statistical facial features to identify fraudulent faces. The pictures come from three distinct sources. Real images were directly gathered using camera capture, whereas fake ones were obtained by photographing printed photos. The user's input frame is taken from a live video feed. For additional feature extraction, the input image is preprocessed. The extraction of color and statistical information occurs during preprocessing. Therefore, both color and a grayscale image are needed. The HSV color space is used to extract the color characteristics. In order to extract statistical features, the RGB color is changed to grayscale color space. The algorithm used to identify faces in the frame is called the Haar cascade classifier. The model is initially trained using the positive (face) and negative (non-face) images. Finally, using a convolutional mask, features were retrieved. KNN (K-nearest Neighbor) classifiers are used in classification to distinguish between real faces and fraudulent images. K-Nearest Neighbor and Support Vector Machine (SVM) algorithms have been used to test the suggested system's accuracy. In order to visualize the data, the classification learner is fed the collected data or a comparison between the real face and a fake face. Accuracy for the SVM and KNN algorithms is 77.41% and 97.69%, respectively. The OpenCV library is used to implement the suggested system

[9]Ying Wu proposed Optical Flow-based analysis.The author presented the method based on an optical flow field. It examines the variations and features of optical flow produced by 2D planes and 3D objects. The four main movement types—translation, rotation, travelling, and swing—combine to make up the motion of an optical flow field .The first three fundamental categories, according to the scientists, provide optical flow fields for 2D and 3D images that are quite similar.The fourth category is what actually alters the optical flow field. The fundamental tenet of their strategy is that the optical flow field for 2D objects may be represented as a projection transformation. To ascertain whether or not the test region is flat, the optical flow enables the deduction of the reference field. To do it, the variance of optical flow fields is computed. This discrepancy is mentioned as a criterion to determine whether a face is a real face or not. On three groups of sample data, the experiment was run. The first group consisted of 100 printed face images that were translated and randomly curled; the second group, 100 images from group 1 that were folded and curled prior to the test; and the third group, faces of real individuals (10 people, each 10 times) making gestures like swinging, shaking, and other similar motions. For 10 seconds, the experiment was run by the authors. 30 frames per second were sampled by the camera. Each 10 frames had the calculation done. As illustrations, the findings were produced in the same manner for each group ((a)-group1, (b)-group 2, and (c)-group3).

Table- I: Comparison on Face Liveliness

Paper Title	Year of Publish	Authors	Dataset	Accuracy
1.Leveraging large face	2017	Boris Knyazev	Face, Speech	72%

recognition data for emotion classification				
2.Wasserstein CNN: Learning Invariant Features for NIR-VIS Face Recognition	2018	Ran He	Face	97.4%
3.Face and Gender Recognition System Based on Convolutional Neural networks	2019	Yuxiang Zhou and Hongjun Ni	Face, Gender Features	93.22%
4.Effect of Super Resolution on High Dimensional Features for Unsupervised Face Recognition in the Wild	2017	Ahmed ElSayed, Ausif Mahmood, Tarek Sobh	Face	-
5.How does the transformation of an avatar face giving a favorable impression affect human recognition of the face	2018	Momoko Hada, Ryoko Yamada and Shigeru Akamatsu	Face	-
6.Face liveness detection based on texture and frequency analyses	2012	G. Kim, S.Eum, J. K. Suhr, D. I. Kim, K. R. Park, and J, Kim	Face Texture	87.54%
7. Shape- Based Eyes Blinking Detection and Analysis	2016	Zeyd Boukhers , Tomasz Jarzynski Florian Schmidt	Face, eyes	70%
8.Face Liveness Detection Using Machine Learning	2019	Sanjay Ganorkar, Supriya Rajankar,Gaurav Rajpurohit	Face	97%
9.Face Liveness Detection Using Optical Flow-based analysis	2013	Ying Wu	Face	-

III. CONCLUSION

This work provided an overview of different approaches of face liveness detection. It presented a categorization based on the type of techniques used and types of liveness indicator/clue used for face liveness detection which helps understanding different spoof attacks scenarios and their relation to the developed solutions. A review of most interesting approaches for liveness detection was presented. The most common problems that have been observed in case of many liveness detection techniques are the effects of illumination change, effects of amplified noise on images which damages the texture information. For blinking and movement of eyes based liveness detection methods, eyes glasses which causes reflection must be considered for future development of liveness detection solutions. Overall we found that Wasserstein CNN: Learning Invariant Features for NIR-VIS Face Recognition by Ran He and Detection for Face Recognition using Ada-boost Haar Cascade algorithm by Sanjay Ganorkar, et. al more efficient..

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