

EIGEN FEATURE EXTRACTION AND CLASSIFICATION BASED DESIGN FACE SPOOF DETECTION METHOD

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Abstract

The current notoriety that differentiating proof of facial instances has achieved among various biometric systems has led to a major development in this field. The security of such systems, however, may be a major problem given that it has been demonstrated in several studies that systems that deal with distinguishing evidence are defenceless against a variety of assaults, including spoofing attempts. Spoofing is the ability to trick a biometric system into mistaking an unauthorised client for a legitimate one by utilising a variety of techniques to present an exact clone of the initial biometric attribute to the item that is being detected. An innovation in picture processing can handle data that has been saved as pixels. The biometric system's facial recognition function innovates by using brain networks. The biometric technologies are impervious to the face spoof attack. Face detection systems are a vast category of the classification and artificial intelligence systems. This audit research addresses the order calculations for face detection and explicit boundary analyses.

Keywords: *biometric system, Detection, Face Spoof, Feature Extraction, spoof attack*

I. INTRODUCTION

Biometric character systems are gaining popularity in today's culture because to their difficulty in obtaining, high accuracy rate, and ease of use for consumers. These methods rely on individual variations in recognisable physical or behavioural traits. The susceptibility to false instances that is observed during the photo capture phase in biometric systems has risen with

mechanical improvement. In applications like PC/cell phone login, identifiable verification cards, border and ID control, face ID is the method that is most frequently used. With this biometric attribute, the appearance of the face acts as a key to identify a particular person in a group of people.

The greatest distinguishing characteristics that may be utilised to tell one person from another are their faces. The most crucial piece of advice is for everyone to look after their family and friends. Because to advancements in image technology, our brains can now recognise faces in photographs. As long as our faces are on documents like passports, ID cards, driver's licences, and student IDs, this task will serve as society's primary means of establishing our identity. As technology continues to progress, automated methods for facial recognition are becoming more and more common. [1] The advanced PC can carry out a range of difficult activities, including as identifying and categorising diseases as well as establishing and authenticating people's identities. With varied levels and types of safety limitations, facial recognition is being employed in a range of contexts. The government makes use of removable gadgets to keep an eye on behaviour in risky locations. Airports, corporations, and many other locations use dynamic, updated entrance control systems. Certain commonly used uncalibrated technologies provide consumers more control over the environment around their activities, such as PC open projects and mobile phone ID programmes. Yet, face spoofing assaults have the capacity to theoretically and really deceive apparent face recognition systems. The system's camera caught a cunning customer's face, which made it simpler to evade a dependable confirmation component. When you consider how many individuals share their images online for free, especially in unauthorised networks, the issue becomes much more significant. Without knowing anything about the client, an attacker may come across a sizable number of excellent images and utilise them to carry out the attack. By adding a second security layer to the system known as the enthusiasm locator or face spoofing finder, the corporation may lengthen the validation period and weak point. Despite the fact that there are many different technical solutions for this layer, virtually all of them require a current system with several cameras and, unexpectedly, different kinds of sensor.

An ANN might be a natural system made up of a variety of neurons. Fake brain organisations (ANN) are developed by concentrating on a creature's primary sensory system. The ANN is a versatile type of AI since it is an organic brain network that aids in the development of creature

minds. A figure that shows neurons as na curves in the chart's hubs might be used to concentrate on how the brain is organised. We may imagine the brain as an artificial intelligence (AI) system that explains how neurons work. The human cerebrum is made up of neurons. Hence, electrical and synthetic motivations are transmitted by the human mind. These neurons are linked to neurons in other areas of the body via neurotransmitters, which enable the transmission of messages. A fake brain network is known as data science. Similar to how the human brain analyses data, artificial neural networks (ANN) are used to organise data, forecast predicted returns from given information, and define groups of data. An electronic model called an ANN uses information from a variety of sources and results to perform in a certain way. [2] ANN use a variety of degrees of numerical computation to interpret the data. There are a tonne of fictitious neurons or units in this design. The information layers will receive it from the outside world, pass it via at least one secret layer, and then send it to the result unit, where the organisation will handle it.

II. REVIEW OF LITREATURE

Mr. Kaustubh D. Vishnu [2017] claims that a biometric system plays an immediate part in the liveness testing of face spoof detection. This method should be adaptable to any spoofing attacks since the body and face prints are coordinated. By utilising pre-existing datasets in this approach, we produced outstanding datasets. It is connected to three face features and a five-figure print picture. There were five preparation and testing tests for each of these datasets. [3] Analyzing a preparation set might identify 40% of incorrect coordination; the data gained is helpful for brain network generators. In order to distinguish between faces, this information is compared to existing data sets.

In order to determine the variety surface of the information picture in 2019, Shatish Balaji R et al. presented a survey. The initial picture adhered to the idea of l^*a*b diversity space. This model allows for the extraction of a few surface and damaged features from the picture, and the VGG7 CNN model is then used to analyse the data. While the perceived spoofing accuracy is 95%, the actual picture's accuracy is estimated to be 88%. While distinguishing between actual and phoney faces in a photograph, the (VGG7 CNN) engineering produced excellent accuracy. in a setting with consistent lighting. In some low-light scenarios, it can't reliably guess the face. With Pig, a photo's face may be cropped. This actually signifies that utilising

the VGG7 convolutional neural network model instead of models like SVM calculated relapse and KNN would produce superior results. Hence, this technique may have provided the best facial recognition results when used for security. The described method is commonly used to defend against spoof attacks on devices and documents.

L. Convolutional neural networks were proposed by Ashok Kumar et al. in 2019 as a method for identifying fraudulent faces. The picture is meant to serve as a CNN structure's input. As we employed the technique of freely training the fake and genuine face dataset, the system can quickly and accurately identify between real and fake photos when given an input picture. The main reason for the brain layers' superiority in the detection of fake pictures is their plasticity. Due of its creativity, face acknowledgment is the most widely used strategy. We must make sure that principal live face photos are utilised in order to correctly allow access to private assets[4]. But, by simulating the faces of actual clients in three dimensions, replaying videos, and utilising photographic assaults, programmers undermine this method. To stop these frauds, numerous strategies have been devised. This concept proposes a way to locate the fake faces by employing a brain structure. To prepare the brain's organisation, one develops their own databases of false and actual visuals. For the purpose of accurately determining the outcome, the two datasets are freely constructed.

The pixel-wise picture layout approach developed by Dr. A. Usha Ruby et al.[2020] combines the previously stated double cross entropy misfortune with CNN, which works as an auto encoder. This investigation demonstrates that when CNN is paired with a double veil and the pixel-wise order approach, it is able to locate each worldwide recurrence (T-F) receptacle across all pictures. This cover treats each T-F receptacle as a multi-name pixel. It does this by fusing a delicate max classifier with a paired cross entropy misfortune capability. The best outcomes are within our reach.

A method for face spoof detection using VGG face design was described by Balamurli K et al in [2021]. For security reasons, this model is used to validate an unauthorised individual. Even on its own, the company's facial recognition technology is notable and prone to being fooled by fake photos and videos. This approach denoises the perceived face before completely switching it over to the YCbCr and CIELUV variety models, taking into consideration the extraction of the face's implanting in each variety space. This method has a 99.6% accuracy

rate and a 99.5% spoof detection rate[5]. With a 99.6% accuracy rate, the help vector classifier (SVC) can identify between genuine and false faces. In the YCbCr and CIELUV variety space, the VGG face model makes it simpler to discriminate between a real and artificial face. In order to prevent spoofing, Zhenqi Xu et al. introduced a brain network engineering in 2015 that comprises the addition of an LSTM layer above a convolutional layer. We can erase a feature completely and locally when we consider the worldwide design of the information grouping. LSTM-CNN design beats both traditional hand-made features and traditional CNN engineering, according to an investigation of a CASIA dataset. By utilising LSTM (long momentary memories) units, this system is good for face anti-spoofing. Moreover, it uses convolutional approaches to distinguish between a few features of dense neighbourhoods. For the (CASIA) dataset, this model performs better than the combined CNN engineering (5.93% and 7.34%) as well as hand-crafted features (5.93% to 10.0%).

In 2016, Litong Feng and colleagues created an adversary of spoofing method to handle different spoofing attack scenarios. Several liveness qualities may be effectively coupled using a bottleneck feature combination approach. To produce judgements at a higher level, the bottleneck features of convolutional brain organisations (CNN) are eliminated. The bottleneck feature is integrated to offer information to the model, and this combination model performs with a flat out awareness of 98.33%. 99.22% forthright absolute accuracy and 99.49% outright explicitness are both achieved.

III. PROPOSED ANTI-SPOOFING METHOD

After a quick review, even the natural eye could find it difficult to tell the difference between the two scenarios, as demonstrated by a straightforward visual link between a parody and a real facial image of a similar person.

In any case, there can be very tiny variations between the real and fake photographs.

[6] Figure 1 shows how face representations created from printed photographs could first resemble those of actual individuals. Finding a group of distinctive characteristics that permits the development of an appropriate classifier to differentiate between genuine and fake faces is the first step in the interaction process. Nevertheless, optical phenomena like reflection and

refraction, which might generate considerable variations between the genuine face and the attack spoof images

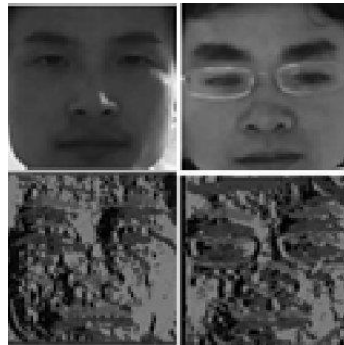


Figure 1: an example of a face image from the CASIA database. First column, genuine face, left to right Cut the column two photo attack. Attack with a Warped Picture in Column 3 attack face in the video in column 4. The centre row shows the depth maps of the different faces. The bottom row shows the GBP texture for the depth maps.

Several materials are missing (such as graphic paper or an electronic display). It is wise to expect that authentic hacks and spoof attacks will have recognisable external features. Figure 2 shows the general flow of the recommended strategy in this study. [7] The spoofing detection stage is separated from the face acknowledgment stage. When spoofing is being detected, the info face is photographed.

Before extracting GBP features, the defocus profundity measure is finished for the changed information face. The SVM classifier is then instructed on how to tell a phoney face from an actual one. After it has been determined that the data is accurate, the acknowledgement stage may now recognise the facial ID. Further face identification has been accomplished using Additional surface characteristics that are comparable.

Depth Map estimation

Depth recovery is essential in computer vision and computer-aided design. We can utilise the defocus cue to gauge depth thanks to the precision with which light-field cameras can operate together. In this work, we tackle the difficult challenge of false-positive face recognition by reconstructing depth from a single defocused picture. The defocus obscure sum may be calculated using the slope % of the information and yet another obscured pictures after the

information defocused image has been reburied using a Gaussian bit. You may recover the whole depth guide of the face by generating the haze sum at edge positions over the entire image. Figure 3 displays examples of actual and synthetic faces as well as contrasts between the defocused profundity map and GBP feature space. The false face plainly matches the actual one quite closely, but profundity maps and space images show key discrepancies that let us to tell the fake from the real.

The impacts of additional edges, noise, and loose edge area are unaffected by the robust approach for measuring opacity that depends on the Gaussian slope %. With just one picture, this technique may create the defocus profundity map with nearly any alteration or standardisation. The following formula may be used to determine the magnitude of the inclination for the creator's 2D isotropic Gaussian portion-based re-obscuring of the facial images:

$$||\nabla_i(x, y)|| = \sqrt{(\nabla_i(x^2)) + (\nabla_i(y^2))}$$

The developers configured the reburied to be 1 in the execution when the slants in the x and y headings are (and (The edge detection is finished utilising Watchful edge identifier. The camera response bend in this artwork is thought to be straight. A defocused profundity map may be made by analysing the haze scales at each edge point. So, it is possible to construct a perceptible profundity contrast between the false and actual photographs using the profundity maps generated by our algorithm, which are clearly shown in figure 3. It has been shown that this method may provide more accurate depth maps when compared to older ones and that it is impervious to noise, improper edge alignment, and encompassing edge obstructions.

a) Sparse Representation Classifier (SRC)

Noise will undoubtedly interfere with the presentation of nearest neighbour (NN) classifiers since they only employ the closest neighbour of an image in the preparation information to forecast the mark of the picture to be tested. By taking into account all of the photos from a comparable classification, Nearest Subspace (NS) allocates the test image to the class with the least degree of remaking error. Yet when courses complement one another in their areas of expertise, NS is generally not going to be fascinating. These issues were addressed by Wright et Alsparse's coding-based face acknowledgment system, which can autonomously select

which pictures from the preparation set to move closer to the test image. Their strategy is brilliantly executed and impervious to noise, distraction, and bustle. The distance between a test and a preparation test should be considered rather than being selected at random since the preparation tests are often not uncorrelated. The meagre approach employs altering distance to define the test after directly combining all of the practise exams to address it as the test. The method settles a straight system to obtain the coefficients of the direct mix. Assuming that the test belongs to the same category as the preparation test with the smallest distance, the technique is then used to determine the distance between the test and the result of multiplying each preparation test by the appropriate coefficient. The technique carefully alters the k-NN classifier and considers the link between the numerous preliminary tests in order to improve order exactness.

b) Face Recognition Using Gbp

The face recognition assignment will begin to recognise the test input facial image after the initial image has been recognised. The SRC classifier interprets the properties that were taken from the grayscale input picture. A good feature extraction approach, which also condenses the original sign into a limited number of boundaries, contains the fundamental traits required to identify related classes. In fact, adding too many flaws might make it harder for people to recognise you. Many efficient feature extraction methods have been demonstrated in the writing. In the mathematical feature-based strategy to manage face recognition evidence, the qualities of the features and their connections (such as regions, distances, and points) are employed as descriptors. In any case, the critical information that was on the surface of the face was not retrievable using our method. The innovative appearance-based neighbouring feature descriptor GBP, which is proposed in this work as a solution to the face recognition issue, is also broadened to address this issue. Section II.B explains the strategy. In a nearby 3 by 3 pixel region, it gathers a lot of underlying and textural data and isolates test picture features that stand out as being especially clear and undisturbed by the imaging environment. Grayscale picture samples from the NUAA data collection are shown in Figure 4 along with the applicable GBP surface trademark. The example shows how the GBP function radically alters the look and textural elements of each individual photo. Exploratory results show that when combined with the SRC classifier for face recognition, the recommended technique is viable.

IV. EXPERIMENTAL RESULTS

Here is a summary of how well our proposed method for identifying and comprehending face spoofing performed. In our testing, we employed the widely known, industry-standard NUAA face fraud information source as well as the CASIA Attack Data Collection. [8] Both the real client face and the false client face must be considered in the variety scale when preparing and executing a two-class test for spoofing detection. Just the client face organiser with 15 classes from the NUAA data set is considered at the acknowledgement stage.

a) Results on NUAA for face spoofing detection

This part displays the NUAA fraud data collection [4], which is hostile to faking and employs photos of various sizes as attacks. Photographs record both moving and stationary pictures of subjects. Certain standard cameras with a resolution of 640 x 480 pixels are utilised to capture the photographs for each topic in each meeting. To compile a picture album

No. of Tanning image	Detection Rate in (%)
120	2.3
210	3.6
350	4.5
360	5.2
410	6.9
520	7.2
660	8.3

Table 1: Spoofing detection rate versus number of training/testing images on the NUAA imposter database

First, tests were taken with a standard Group camera in high target, making sure that each subject's face occupied at least 2/3 of the whole image. 15 individuals who were the targets of actual invasions and attacks employing photo- and laser-quality prints are included in the data bank.

This section explains how to use the NUAA data source to do a preliminary study of our recommended method for Face Spoofing Detection.

[9] The 15 subjects' photos have been edited and downsized to 64x64 pixels. Separately, 15 persons were picked for 2383 actual face tests and 3912 false face tests utilising the NUAA data source. We conduct the experiment by underestimating the quantity of one image preparation and keeping the remaining picture as a test picture in order to assess the presentation of the recommended strategy as a component of picture preparation. By increasing the quantity of preparation images to 3148, the testing was also finished. It should be obvious that our recommended method offers a respectable distinguishing proof rate on the benchmark even with just 10 practise photos for each class. data sourced from NUAA. Also, exploratory results show that increasing the number of photos taken increases the precision of our calculation. As seen in figure 5, when the whole number of photographs in the NUAA data set are randomly and evenly divided into preparation and testing photos, our recommended strategy produces a higher acknowledgement rate of 99.26%. Tan et al findings . 's and Jukka et al findings . 's showed acknowledgment rates of 94% and almost 100%, respectively. Moreover, it outperforms those results.

Method	Error Rate (%)
Regular LBP	3.6
LBP+ Depthmap	4.6
GBP	5.9
Proposed Method	6.8

Table 2: Error Rate (%) Of SpooF Detection On The Casia SpooF Attacks

SpooFing attack	Depth map	GBP	Proposed Method
Video attack	5.36	2.36	3.63
Warped photo attack	5.22	3.23	4.25

Cut photo attack	6.22	4.22	5.33
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Table 3: Error Rate (%) Of Spoof Detection On The Casia Attacks

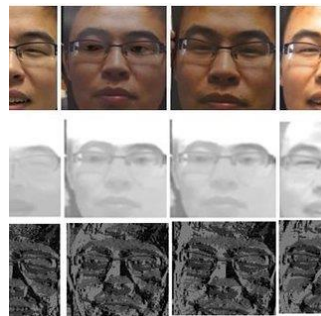


Figure 2: CASIA employs a number of different fake face attacks, including the following: (1) the attacker hides behind the cut photo on the left and blinks; (2) a second intact photo is moved up and down in front of the cut photo; and (3) the video attack on the right.

There are also assaults on the face. (1) To resemble facial life, the perpetrator of a twisted photo attack purposely alters a photograph of an unharmed person. Unblemished instead of sliced photograph attack refers to the absence of an end segment in the image. (2) To create the illusion of flickering, a cut image assault eliminates the subject's eye regions. An offender hiding behind and peering through the holes is depicted in Figure 6. (3) In a video assault, an iPad is used to broadcast genuine footage in high definition. Be warned that the first high target recordings (1280x720) are limited by the iPad's screen resolution, and the device should certainly lower them[10]. To give verifiable faces, fifty people were assembled. Each person is captured in a distinct typical setting; there is no fabricated climate unity. They are told to walk about rather than sit motionless during the recording. It's necessary to offer facial movement in the same manner as a test reaction approach used in facial movement detection systems is supplied since from some perspectives, facial movement acts as a critical liveness signal for antispoofing. The movement kind of flickering is favoured over others like head development and mouth development because it is more natural and straightforward to utilise.

Ten members of CASIA had images taken of each of the three attack faces in order to evaluate how accurate our computation was. 100 genuine faces and 300 fictitious faces are mixed for evaluation. The pictures picked for evaluation and practise are chosen at random. The face spoofing detection error rate for three attacks on the CASIA data set is shown in Tables I and II. Table II presents findings for particular picture attacks, whereas Table I uses data from all spoof attack faces. I features only from depthmap, II features only from LBP and Depthmap features from LBP, III features solely from GBP, and IV proposed approach, i.e., GBP surface feature acquired from depth guide of the face, all have results. Our proposed method yields an error rate of 19:96% despite the complexity of the CASIA data set, highlighting the significance of the depth map paired with the LGP surface feature.

Results on NUAA in Face Recognition

Our proposed GBP surface features have been enhanced to give greater face acknowledgment following spoofing detection. We randomly selected 2383 genuine faces and 3912 false faces from the NUAA information source to complete the face recognition job, utilising half of the photos for testing and preparation. 64×64 pixels is the reduced size of the original picture. Organization of features is done using the SRC classifier. The benchmark facial acknowledgement calculation's result is compared to the FR using the NUAA data set.

Tanning Sample	Recognition Rate (%)
2.6	2.3
3.5	4.2
4.2	4.9
5.9	5.2
6.2	5.6
6.9	6.5
7.2	7.2

Table 4: Performance comparison of Face Recognition on NUAA imposter Database with state of the art methods

Five analysis runs were done, and the findings were plotted, according to the acknowledgment result. [11] It has been noticed that the proposed method's acceptance rate for GBP is 99.06%. According to preliminary findings, the recommended method effectively and accurately recognises faces on the NUAA faker knowledge set when paired with the SRC classifier. The relevance of these components is illustrated by Figure 6's comparison of the GBP surface properties to the best-in-class method.

V. CONCLUSION

Face spoofing detection has lately acquired notoriety and is drawing a lot of interest in the field of face identifying evidence. In this article, we suggested a novel method for face anti-spoofing detection that uses slope paired examples (GBP) to isolate significant surface data from the defocused depth evaluated image. The standard defocused depthmap evaluation technique, an estimation of the image quality, and variations in light reflection served as the inspiration for this method. [12] We put up a technique that could tell authentic facial photos from fake ones. Face prints frequently contain printing quality issues, which may be easily found by taking measurements of the depthmap and utilising detailed surface samples. A human face is not considered to be a hard thing, despite the fact that a photograph may be, therefore they reflect light differently. According to this study, Quality LBPnet, another convolutional brain network approach, may be used to detect face spoofing in the context of LBP. For the NUAA dataset, our technique fared better than other state-of-the-art methods. [13] The recommended method boosts system security by offering high accuracy (98%), a decreased Equivalent Mistake Rate, and enhanced spoofing attack detection, according to a few assessment criteria.

VI. FUTURE SCOPE

The model may then be developed and tested using consistent datasets, and efforts can also be made to produce a small model of the acquired biometric system. [14] This system can be used for a variety of purposes, including those related to the hospitality, military, finance, aviation, and security industries, among others. This may also be used in the medical services sector, for instance in ICUs and other limited spaces where the distinct experts and specialists can access the records of patients as well as their reports, given that daily misbehaviour is on the rise in the electronic medical care system[15].

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