An Empirical Analysison Liveness Discovery Strategy for Face Recognition Settled on ML

[1]Venkatesha G, Dr. M.K.Agarwal
PhD, Research Scholar, roopadarshi@gmail.com

ABSTRACT

Face Spoofing is a sort of assault on a face acknowledgment framework. What might occur assuming any unapproved client intentionally attempted to get to the face acknowledgment framework? Such a client might have a photograph or video on their cell phone that they could consider up to the camera answerable for performing face acknowledgment. In those circumstances, the camera can without much of a stretch give access, in any case it will prompt an unapproved client sidestep the face acknowledgment framework. Our proposed framework ready to detect Spoof and genuine countenances. In this framework, we regarded face caricaturing identification as a twofold arrangement issue. A Caffe Face indicator is utilized to find the face ROIs. Then, at that point, the removed elements are prepared utilizing VGGNet-esque CNN engineering. We prepared a Convolutional Neural Network equipped for recognizing genuine countenances from counterfeit/caricature faces. Face acknowledgment is a broadly utilized biometric approach. Face acknowledgment innovation has grown quickly as of late and it is more straightforward, easy to use and advantageous contrasted with different techniques. However, face acknowledgment frameworks are powerless against parody assaults made by non-genuine countenances. It is a simple method for mocking face acknowledgment

frameworks by facial pictures, for example, representation photos. A protected framework needs Liveness recognition to make preparations for such mocking. In this work, face liveness identification approaches are sorted in light of the different kinds strategies utilized for liveness discovery. This arrangement helps understanding different satire assaults situations and their connection to the created arrangements. An audit of the most recent works with respect to confront liveness location works is introduced. The fundamental point is to give a basic way to the future improvement of novel and more got face liveness location approach.

Keyword: Liveness Detection, Convolutional Neural Network, Face recognition, Biometrics, , Spoofing.

1. INTRODUCTION

It is nothing unexpected that cybercrime is on the ascent in our expanding computerized world. Many organizations are presently investigating biometric face acknowledgment as suitable security arrangement. The overall population has tremendous requirement for safety efforts against parody assault. Biometrics is the quickest developing portion of such security industry. A portion of the recognizable methods for distinguishing proof are facial acknowledgment, finger impression acknowledgment, penmanship check, hand calculation, retinal and iris scanner. Among these procedures, the one which has grown quickly as of late is face acknowledgment innovation and it is more straightforward, easy to understand and advantageous contrasted with different techniques[1]. This creative innovation shows a great deal of

guarantee and change the manner by which we can get to touchy data. Be that as it may, however encouraging as facial acknowledgment seems to be it has blemishes. Client photographs can without much of a stretch be found on interpersonal interaction locales and pictures can be ridiculed. This is the place where the need of antispoofing becomes possibly the most important factor. Face against ridiculing is the undertaking of forestalling bogus facial confirmation by utilizing a photograph, video/substitute for an approved individual's face [2].

Biometrics is the innovation of laying out the character of an individual in light of the physical or conduct credits of the individual. The significance of biometrics in current culture has been fortified by the requirement for enormous scope character the board frameworks whose usefulness relies upon the exact derivation of a singular's personality on the structure of different applications. A few instances of these applications incorporate sharing organized PC assets, conceding admittance to atomic offices, performing distant monetary exchanges or loading up a business flight [3]. The principle assignment of a security framework is the check of a singular's personality. The essential justification behind this is to keep frauds from getting to safeguarded assets. General strategies for security objects are passwords or ID cards components, however these procedures of character can without much of a stretch be lost, hampered or might be taken in this way sabotage the expected security. With the assistance of physical and natural properties of people, a biometric framework can offer greater security for a security framework [4].

Liveness identification has been an exceptionally dynamic examination theme in unique mark acknowledgment and iris acknowledgment networks lately. However, in face acknowledgment, approaches are a lot of restricted to manage this issue. Liveness is the demonstration of separating the component space into live and non-living. Shams will attempt to present countless satirize biometrics into framework. With the assistance of liveness location, the exhibition of a biometric framework will get to the next level. It is a significant and testing issue which decides the dependability of biometric framework protection from ridiculing. In face acknowledgment, the standard assault strategies might be ordered into a few classes. The grouping depends on what confirmation evidence is given to confront check framework, for example, a taken photograph, taken face photographs, recorded video, 3D face models with the capacities of flickering and lip moving, 3D face models with different looks, etc. Hostile to parody issue ought to be all around tackled before face acknowledgment frameworks could be generally applied in our regular routine [5] [6].

2. LITERATURE SURVEY

There are many methodologies executed in Face Liveness Detection. In this part, probably the most intriguing liveness location techniques are introduced.

2.1 Frequency and Texture based investigation

The essential intention is to separate between live face and phony face (2-D paper veils) as far as shape and detailedness. The creators have proposed a solitary picture based phony face identification strategy in view of recurrence and surface investigations for separating live faces from 2-D paper covers. The creators have completed power range based strategy for the recurrence investigation, which takes advantage of both the low recurrence data and the data dwelling in the high recurrence districts. Additionally, depiction strategy in light of Local Binary Pattern (LBP) has been executed for investigating the surfaces on the given facial pictures. They attempted to take advantage of recurrence and surface data in separating the live face picture from 2-D paper covers. The creators recommended that the recurrence data is utilized due to two reasons. Initial one is that the distinction in the presence of three dimensional shapes, which prompts the distinction in the low recurrence locales which is connected with the light part created by and large state of a face. Furthermore, the distinction in the detail data between the live faces and the covers sets off the inconsistency in the high recurrence data. The surface data is taken as the pictures taken from the 2-D items (particularly, the light parts) will more often than not experience the ill effects of the deficiency of surface data contrasted with the pictures taken from the three dimensional articles. For include extraction, recurrence based element extraction, Texture-based component extraction and Fusion-based element extraction are being executed. For removing the recurrence data, from the get go, the creators have changed the facial picture into the recurrence space with assistance of 2-D discrete Fourier change. Then, at that point, the changed outcome is partitioned into a few gatherings of concentric rings with the end goal that each ring addresses a comparing area in the recurrence band. At last, 1-D component vector is

procured by joining the normal energy upsides of the multitude of concentric rings. For surface based component extraction, they utilized Local Binary Pattern (LBP) which is quite possibly the most well known procedure for depicting the surface data of the pictures[7]. For the last one for example combination based element extraction, the creators uses Support Vector Machine (SVM) classifier for learning liveness identifiers with the component vectors produced by power range based and LBP-based techniques. The combination based technique extricates an element vector by the blend of the choice worth of SVM classifier which are prepared by power range based element vectors and SVM classifier which are prepared by LBP-based component vectors. The creators have involved two sorts of data sets for their analyses: BERC Webcam Database and BERC ATM Database. Every one of the pictures in webcam data set were caught under three different brightening conditions and the phony appearances (non-live) were caught from printed paper, magazine and personification pictures. Exploratory aftereffects of the proposed approach showed that LBP based strategy shows more encouraging outcome than frequencybased technique when pictures are caught from prints and cartoon. By and large, the combination based strategy showed best outcome with mistake pace of 4.42% contrasted with recurrence based with 5.43% and LBP-based technique with 12.46% blunder rate. Comparative procedure of face ridiculing location from single pictures utilizing miniature surface examination was executed . The key thought is to accentuate the distinctions of miniature surface in the component space. The creators take on the nearby double examples (LBP) which is a strong surface administrator, for depicting the miniature surfaces and their spatial data. The vectors in the element space are then given as a contribution to a SVM classifier which decides if the miniature surface examples

describe a phony picture or a live individual picture. The initial step is to recognize the face, which is then edited and standardization is done and changed over into a 64 × 64 pixel picture. Then, at that point, they applied LBP administrator on the standardized face picture and the subsequent LBP face picture is then partitioned into 3×3 covering areas [8]. The nearby 59-container histograms acquired from every district are then figured and gathered into a solitary 531-canister histogram. Then, at that point, two different histograms acquired from the entire face picture are figured utilizing LBP administrators. At last, a nonlinear SVM classifier with spiral premise work part is utilized for deciding if the info picture is a phony face or live individual picture. The trial results showed that LBP has the best presentation with equivalent blunder rate (EER) of 2.9% in correlation with other surface administrators like Local Phase Quantization and Gabor Wavelets with EER of 4.6% and 9.5% individually. One more strategy for surface put together liveness discovery based with respect to the investigation of Fourier Spectra of a solitary face picture or face grouping picture was presented.[9]. Their strategy depends on design and development data of live face. Their calculation depends on two standards: first, as the size of the photograph is more modest than that of live face and the photograph is level, high recurrence parts of photograph pictures is not exactly those of genuine face pictures and furthermore, regardless of whether a photograph is held before a camera and is moving, as the demeanors and stances of the face contained in the photograph doesn't differ, the standard deviation of recurrence parts in an arrangement is little. The creators have proposed that a powerful lifestyle choice face discovery is to examine 2D Fourier spectra of the info picture. They determined the proportion of the energy of high recurrence parts to that of all recurrence parts as the comparing high recurrence

descriptor (HFD). As indicated by the creators, high recurrence descriptor of the live face should be in excess of a sensible limit Tfd. The high recurrence parts of a picture are those whose frequencies are more noteworthy than two third of the greatest span recurrence of the picture and whose extents are likewise more prominent than an edge Tf (by and large, the size of high recurrence parts brought about by the fraud interaction is more modest than that of unique picture.). The creators have discovered that the over the above strategy will be crushed assuming an exceptionally clear and huge size photograph is utilized to trick the framework. To take care of this issue, movement pictures were taken advantage of for the live face location. Along these lines, by means of observing fleeting changes of facial appearance over the long run, where facial appearance is addressed by an energy esteem characterized in recurrence area, is a compelling way to deal with live face discovery. The creators have proposed a calculation which is of three stages to tackle this issue. In the initial step, a subset is built by separating picture from an info picture succession each four pictures. In the subsequent advance, for each picture in such subset, an energy esteem t is figured. The recurrence elements descriptor (FDD) that is the standard deviation of the subsequent banner worth, is determined for the portrayal of fleeting changes of the face. Contrasted with different works, which search for three dimensional profundity data of the head, the proposed calculation enjoys many benefits considering present realities simple to compute [10].

Table 1. Experimental results of live face detection

Image Sequence		Frequency Dynamics descriptor			High Frequency descriptor		
		Mean	Min	Max	Mean	Min	Max
Live face	200 images	960	718	1490	0.7197	0.4011	2.0544
Fake face	40 images (48x33mm)	286	233	376	0	0	0
	50 images (76x55mm)	260	186	364	0.0913	0	0.1376
	90 images (124x84mm)	175	91	282	0.3535	0	0.5514
	20 images (600dpi)	249	237	260	0.2803	0	0.3917

2.2 Variable Focusing based examination

The procedure of face liveness identification utilizing variable centering was carried out by Sooyeon . The key methodology is to use the variety of pixel values by centering between two pictures consecutively taken in various centers which is one of the camera capacities. Accepting that there is no large distinction in development, the creators have attempted to observe the distinction in center qualities among genuine and counterfeit countenances when two successive images(in/out center) are gathered from each subject. If there should arise an occurrence of genuine countenances, centered districts are clear and others are obscured because of profundity data. Interestingly, there is little contrast between pictures taken in various concentrations from a printed duplicate of a face, since they are not strong. The essential imperative of this strategy is that it depends on the level of Depth of Field (DoF) that decides the scope of center varieties at pixels from the successively taken pictures. The DoF is the reach between the closest and farthest articles

in a given concentration. To expand the liveness discovery execution, the creators have expanded out focussing impact for which the DoF should be thin. In this technique, Sum Modified Laplacian(SML) is utilized for center worth estimation. The SML addresses levels of centering in pictures and those values are addressed as a changed second request differential channel. In the initial step, two successive pictures by zeroing in the camera on facial parts are being. One is centered around a nose and the other is on ears. The nose is the nearest to the camera focal point, while the ears are the farthest. The profundity hole between them is adequate to communicate a 3D impact. To pass judgment on the level of centering, SMLs of both the photos are being determined. The third step is to get the distinction of SMLs. For one-layered investigation, aggregate contrasts of SMLs (DoS) in every one of segments are determined [11]. The creators discovered that the amounts of DoS of genuine faces show comparable examples reliably, while those of phony countenances don't. The distinctions in the examples among genuine and counterfeit countenances are utilized as elements to identify face liveness. For testing, the creators have thought about False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR is a pace of the quantities of phony pictures misclassified as genuine and FRR is a pace of the quantities of genuine pictures misclassified as phony. The exploratory outcomes showed that when Depth of Field (DoF) is tiny, FAR is 2.86% and FRR is 0.00% yet when DoF is enormous, the normal FAR and FRR is expanded. Accordingly the outcomes showed that this strategy is urgently subject to DoF and for better outcomes, it is vital to make DoF little [12].

2.3 Movement of the eyes put together investigation

The method based with respect to the examination of development of eyes was presented by Hyung-Keun Jee et al. for implanted face acknowledgment framework . The creators proposed a technique for distinguishing eyes in successive information pictures and afterward variety of each eye locale is determined and whether or not the information face is not set in stone. The fundamental supposition that will be that in light of flickering and uncontrolled developments of the understudies in natural eyes, there should be enormous shape varieties. First focus point of the two eyes is recognized in the information face picture. Utilizing distinguished the two eyes, face area are standardized and eye areas are separated. Subsequent to binarizing separated eye districts, each binarized eye areas are thought about and variety is determined. On the off chance that the outcome is greater than edge, the information picture is perceived as live face, if not, it is separated to the photo. For discovery of the eye districts, the creators utilized the way that the power of the eye area is lower than the remainder of face locale assuming the picture is considered as a 3D bend. To observe the eye locale, first, Gaussian separating to the face picture is done, so the smoothened 3D bend is acquired. In the bend, we separate every one of the nearby essentials utilizing the strategy for the angle drop. To decrease the invalid eye applicants, the eye classifier, which is prepared by Viloa's AdaBoost preparing techniques, is utilized. From that point onward, face district is being standardized by about a size and pivot by utilizing focus point of eyes in light of the fact that the info face can shift in size and direction. To diminish the impact of light, Self Quotient Image (SQI) is applied. Subsequent to Normalizing face area, eye locales are extricated in light of the focal point of eyes. Then, at that point, eye areas are binarized to

have the pixel worth of 0 and 1 by utilizing an edge. The edge is acquired from the mean pixel worth of each eye locale. Eye locales from genuine countenances have greater varieties in shape than districts acquired from counterfeit appearances. For ascertaining liveness score of each eye area, Hamming distance strategy is utilized. Assuming two arranged arrangements of pixels are thought about, the Hamming distance is the quantity of pixels that don't have same worth. On the off chance that the normal liveness score is greater than limit, the info picture is perceived as live face and on account of inverse it is separated as a photo. Trial results showed that when liveness score is estimated utilizing Hamming distance, mean score of live face is 30 and that of phony face is 17 which shows that score of live face is plainly more noteworthy than that of phony appearances. Thus, when the edge is set up as 21, the creators accomplished best execution with FAR as 0.01 and FRR as 0.08 [13] [14].

Table 2. Obtained hamming distance

HAMMING DISTANCE OF EYE REGIONS

	Hamming distance		
	Mean	Min	Max
Live face	30	18	47
Fake face	17	10	22

2.4 Optical Flow based analysis

It analyzes the differences and properties of optical flow generated from 3D objects and 2D planes. The motion of optical flow field is a combination of four basic movement types: Translation, rotation, moving and swing. The authors found that the first three basic types are generating quite similar optical flow fields for both 2D and for 3D images. The fourth type creates the actual differences in optical flow field. Their approach is basically based on the idea that the optical flow field for 2D objects can be represented as a projection transformation. The optical flow allows to deduce the reference field,thus allows to determine whether the test region is planar or not. For that, the difference among optical flow fields is calculated. To decide whether a face is a real face or not, this difference is being noted as a threshold. The Experiment was conducted on three groups of sample data. The first group contained 100 printed face pictures that were translated and randomly rotated, the second group contains 100 pictures from group 1 that were folded and curled before the test, the third group consisted of faces of real people (10 people, each 10 times) doing gestures like swinging, shaking, etc. The authors conducted the experiment for 10 seconds. The camera had sampling rate of 30 frames per second. The calculation was done for every 10 frames. Fig. 2 shows examples of each group ((a)-group1, (b)-group 2 and (c)-group3) as well as the results obtained [15] [16].

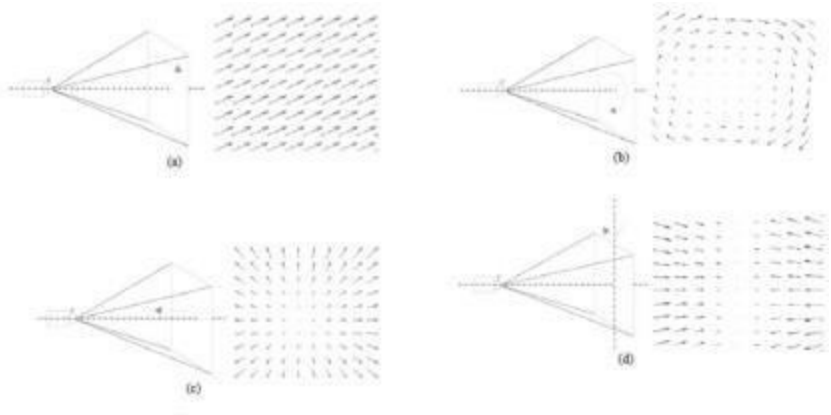
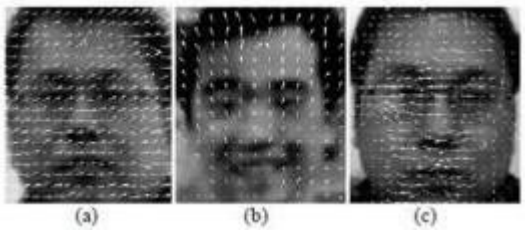


Figure 1: Four basic types of optical flow fields as presented in figure.



Group	T			
	0.2	0.4	0.6	0.8
1st	0.54	0.83	0.86	0.92
2nd	0.45	0.80	0.85	0.89
3rd	1.00	1.00	0.94	0.86

Figure 2. Examples (a)-group1, (b)-group 2 and (c)-group3 and Results: the ratio of successful detection in each experiment (0 to 1).

As displayed in Fig. 2, if the edge (T) is more noteworthy, the proportion of effective recognition will be higher. Yet, at one point the proportion might drop, it should be noticed that the creators didn't make reference to any misleading acknowledgment rates. Another detriment is that light changes will contrarily affect the outcomes as the strategy depends on exact computation of the optical stream field. This strategy will fizzle in the event that the phony face isn't planar for example it will fizzle for 3D items. Subsequently, creators have offered guidance to utilize this calculation with other liveness recognition techniques. A blend of face parts recognition and an assessment of optical stream field for face liveness discovery were presented [17]. This approach can separate between movement of focuses and movement of lines. The creators have proposed a technique which investigates the directions of single pieces of a live face. The data which is being gotten can be utilized to conclude whether or not a printed picture was utilized. This approach involves a model-based Gabor deterioration and SVM for location of face parts. The fundamental thought of this technique depends with the understanding that a 3D face creates a 2D movement which is higher at focal face areas than at the external face districts like ears. In this way, parts which are farther away move uniquely in contrast to parts which are closer to the camera. Be that as it may, a photo produces a steady movement on various face locales. With the data of the face parts positions and their speed, it is feasible to analyze how quick they are comparable to one another [18]. This data is utilized to separate between a live face from a photo. The creators proposed calculations for the processing and execution of the optical progression

of lines (OFL). For this, they have involved the primary Gabor channels which are straight channels for edge recognition. The creators presented two methodologies for the face parts recognition: initial one depends on optical stream design coordinating and model-based Gabor highlight grouping. The subsequent one concentrates Gabor highlights in a non-uniform retinotopic network and arranges them with prepared SVM specialists. The information base which is utilized contained 100 recordings of Head Rotation Shot-subset (DVD002 media) of the XM2VTS data set. All information were cut back to 300x240 pixels. Recordings were cut (3 to 5 casings) and were utilized for live and non-live successions. Every individual's last casing was taken and was made an interpretation of evenly and in an upward direction to get two non-live arrangements per individual. Hence, 200 live and 200 non live arrangements were inspected. The vast majority of the live arrangements accomplished a score of 0.75 out of 1, though the non-live pictures accomplished a score under 0.5. It was likewise seen that glasses and mustaches brought down the score, as they were near the camera. The creators referenced that the framework will be without mistake assuming successions containing just even developments are utilized. By considering a liveness score more noteworthy than 0.5 as alive, the proposed framework isolates 400 test arrangements with mistake pace of 0.75 % [19].

Table 3. Liveness score distribution for live and non-live sequences

Liveness score	# Non-live seq.	# Live seq.
0	148	0
0.25	49	0
0.5	3	38
0.75	0	120
1	0	42

2.5. Blinking based analysis

The blinking-based approach for liveness detection using Conditional Random Fields (CRFs) was introduced by Lin Sun. The authors have used CRFs to model blinking activities, for accommodating long-range dependencies on the observation sequence. Then they compared CRF model with a discriminative model like AdaBoost and a generative model like HMM. Conditional random fields(CRFs) are probabilistic models for segmenting and labeling sequence data and mainly used in natural language processing for its accommodating long-range dependencies on the observation sequence. Blinking activity is an action represented by the image sequence which consists of images with close and non-close state.

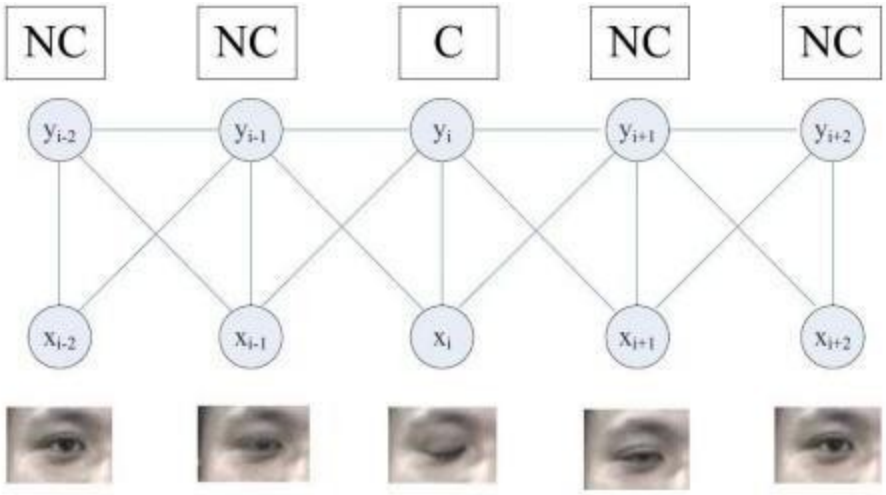


Figure 3. Graphic structure of CRF-based blinking model.

Here we show the model based on contexts of observation of size 3. Labels C and NC are for close state and non-close state respectively. The authors have applied a linear chain structure of CRFs. It has discrete eye state label data yt $\in$ χ = {1, 2, . . . , c}, t = 1. . .T, and observation xt. According to the authors, Half-open state is difficult to define commonly over the different individuals, since the eye size of half-open state depends on the person eye appearance, for example, the open state of a small eye might look like the half-open state of a big eye. As for the blinking model, two state labels, C for close state and NC for non-close (include half-open and open), to label eye states are being employed by the authors. Graphical structure of CRF-based blinking model is shown in Fig. 3. To test their approach, the authors have used video database including blinking video clips and imposter video clips, They used a total of 80 clips which is in blinking video database for 20 individuals, 4 clips for each individual: the first clip includes video without glasses in frontal view, the second clip is with thin rim glasses in frontal view,

the third clip contains video with black frame glasses in frontal view, and the last clip is having video without glasses in upward view [20]. The video clips which are being used are of five seconds' length with 30 fps and size of 320 × 240. The blinking number in each clip varies from 1 to 6 times. To test the ability against photo imposters, the authors have used 180 photo imposter video clips of 20 persons with various motions of photo, including rotating, folding and moving. Using the blinking database, the CRF-based blinking detection is compared with cascaded Adaboost and HMM approaches. The detection rate is shown in Table 2,3,4,5. [21]

Table 4. One-eye blinking detection rate for cascaded AdaBoost, HMM and CRF

Different styles	Cascaded AdaBoost	HMM	CRF($w = 2$)
Without glasses	96.5%	73.7%	98.2%
With thin rim glasses	60.0%	46.9%	68.5%
With black frame glasses	46.9%	39.1%	75.0%
Upward without glasses	52.5%	43.4%	77.0%

Table 5. Two-eye blinking detection rate for cascaded AdaBoost, HMM and CRF

Different styles	Cascaded AdaBoost	HMM	CRF($w = 2$)
Without glasses	98.2%	82.5%	100%
With thin rim glasses	80.0%	63.1%	84.6%
With black frame glasses	71.9%	50.0%	92.2%
Upward without glasses	62.3%	50.9%	100%

Table 6. Live face detection rate for cascaded AdaBoost, HMM and CRF

Different styles	Cascaded AdaBoost	HMM	CRF($w = 2$)
Without glasses	100%	100%	100%
With thin rim glasses	95%	95%	90%
With black frame glasses	80%	85%	100%
Upward without glasses	85%	95%	100%

Table 7. Imposter detection rate for cascaded AdaBoost, HMM and CRF

Cascaded AdaBoost	HMM	CRF($w = 2$)
95%	97.8%	98.3%

Similar technique of blinking-based liveness detection was implemented by Gang Pan. The authors have employed the eye blink behaviors in an undirected Conditional Random Field framework, incorporated with a discriminative measure of eye states for simplifying the complex of inference and simultaneously improving the performance. The author suggested some advantages of eyeblink-based method, some of which are non-intrusion; no requirement of extra hardware .The proposed method has many advantages, one of which is that it allows relaxing the assumption of conditional independence of the observed data. Then the authors have compared their method to cascaded AdaBoost and HMM. The comparison results showed that their approach outperforms the others. However, blinking-based liveness detection has some limitations. It would be affected by strong glasses reflection, which may cover eyes partially or totally. 2.6 Component Dependent Descriptor based analysis The technique of Component-based face coding approach for liveness detection was employed. The authors have proposed a method which consists of four steps: (1) locating the components of face; (2) coding the low-level

features respectively for all the components; (3) deriving the high-level face representation by pooling the codes with weights derived from Fisher criterion; (4) concatenating the histograms from all components into a classifier for identification. The authors found out that significant operational difference between genuine faces and fake ones is that the former are captured by camera once, whereas the latter are obtained by re-capturing images of photos or screens. This will produce their appearance differences in three aspects: (1) Faces are blurred because of limited resolution of photos or screens and re-defocus of camera; (2) Faces appearance vary more or less for reflectance change caused by Gamma Correction of camera; (3) Face appearance also change for abnormal shading on surfaces of photos and screens. At first, the authors have expanded the detected face to obtain the holistic-face (H-Face). Then the H-Face is divided into six components (parts) which includes contour region, facial region, left eye region, right eye region, mouth region and nose region. Moreover, contour region and facial region is further divided into 2 × 2 grids, respectively. For all the twelve components, dense lowlevel features (e.g., LBP, LPQ, HOG, etc.) are extracted. Given the densely extracted local features, a component-based coding is performed based on an offline trained codebook to obtain local codes. Then the codes are concatenated into a high-level descriptor with weights derived from Fisher criterion analysis. Fisher ratio is used to describe the difference of micro textures between genuine faces and fake faces. At last, the authors feed features into a support vector machine (SVM) classifier. For experimentation, the authors have used three different kinds of databases: NUAA Database, CASIA Database and Print-Attack Database. The authors showed that the proposed approach achieved better performance for all the databases [22] [23].

2.7 3D Face Shape based analysis

The novel liveness detection method, based on 3D structure of the face is proposed by Andrea Lagorio . The proposed approach allows a biometric system to differentiate real face from a photo thus reducing the vulnerability. The authors suggested that the proposed approach can be implemented in different scenarios: either as an anti-spoofing tool, coupled with 2D face recognition systems; or can be integrated with a 3D face recognition system to perform an early detection of spoofing attacks. The proposed algorithm computes the 3D features of the captured face data to determine if there is a live face is presented in front of the camera or not. The authors show that the lack of surface variation in the scan is one of the key evidence that the acquisition comes from 2D source. It has a very low surface curvature. Based on the computation of the mean curvature of the surface, a simple and fast method is implemented to compare the two 3D scans. An approximation of the actual curvature value at each point is computed from the principal components of the Cartesian coordinates within a given neighborhood. The mean curvature of the 3D points lying on the face surface is then computed. The authors designed two experiments. In the first one, they used FS and GVS sets. The distribution of the mean curvature values for the two sets was separated, and the value of the False Rejection Rate (FRR), was computed as zero. In the second experiment they used the FS and the Bosforus sets. In order to determine the sensitivity of the algorithm, they perform various experiments with values ranging from 4 to 20. For different values of radius, the value of the False Rejection Rate (FRR) at rank 1 is always equal to zero. Another novel

technique of face liveness detection using 3D structure recovered from a single camera was introduced. The authors have proposed a novel approach for face liveness detection by analyzing the sparse 3D facial structure. The basic idea is that structures from structures recovered from genuine faces usually contain sufficient 3D structure information, while structures from fake faces (photos) are usually planar in depth. From a given facial video or a sequence of images which are captured from more than two viewpoints, facial landmarks are detected and key frames are being selected. Then from the selected key frames, the sparse 3D facial structures are recovered. Then an SVM classifier is trained to differentiate live faces from fake faces. The authors have showed that the proposed approach has many advantages over many previous works. One of the advantages is that the proposed approach is independent of device and can work with various inputs. For experimentation, the authors have collected three databases using different quality cameras to inspect the anti-spoofing performance across different devices. The proposed approach achieves 100% for both classification results and face liveness detection accuracy.

2.8 Binary Classification based analysis

The key approach which the authors have used is that a real human face is different from a face in a photo. A real face is a 3D object while a photo is 2D by itself. The surface roughness of a photo and a real face is different. The authors presented a real-time and non-intrusive method to address this based on individual images from a generic web camera. The task is being formulated as a binary classification problem, in

which, however, the distribution of positive and negative are largely overlapping in the input space, and a suitable representation space is found to be of great importance. Using the Lambertian model, they proposed two strategies to extract the essential information about different surface properties of a live human face or a photograph, in terms of latent samples. Based on these, two new extensions to the sparse logistic regression model were employed which allow quick and accurate spoof detection. For classification, the standard sparse logistic regression classifier was extended both nonlinearly and spatially to improve its generalization capability under the settings of high dimensionality and small size samples. The authors found out that the nonlinear sparse logistic regression significantly improves the anti-photo spoof performance, while the spatial extension leads to a sparse low rank bilinear logistic regression model. To evaluate their method, a publicly available large photograph-imposter database containing over 50K photo images from 15 subjects is collected by the authors. Preliminary experiments on this database show that the method proposed by the authors gives good detection performance, with advantages of realtime testing, nonintrusion and no requirement extra hardware [24].

Although Tan et al. have presented very effective results in their work.The authors overlooked the problem of bad illumination conditions.They extended their work to deal with images even under bad illumination conditions either for spoof attempts coming from a laptop display or high-quality printed images. The basic key is that the brightness of the image captured from LCD screen affects the image in such a way that the high-frequency regions become prone to a “blurring” effect due to the pixels with higher values brightening their neighbourhood. This makes the fake images show less borders

than the real face image. The authors have detected whether an image is a spoof or not by exploring such information. First, they have analyzed the image using Difference of Gaussian (DoG) filter that uses two Gaussian filters with different standard deviations as limits. The basic idea of the authors was to keep the high-middle-frequencies to detect the borders in order to remove the noise. But DoG filtering does not detect the borders properly under bad illumination conditions. For the classification stage, Sparse Logistic Regression Model similar to the model in Tan et al. was used by the authors. To minimize the effects of bad illumination, the image was pre-processed in order to homogenize it, so that the illumination changes become more controlled. The authors have used the contrast-limited adaptive histogram equalization (CLAHE). The main idea of CLAHE is that it operates on small regions in the image, called tiles. The Experimental results for NUAA Imposter Database o and proposed extension for bad illumination by Peixoto et al. [25] [26]:

Table 8. Tan et al. [11] approach

	Min	Mean	Max	STD
Classification Accuracy	85.2%	86.6%	87.5%	0.6%
True Positive Rate	81.9%	82.4%	90.4%	0.6%
False Positive Rate	8.0%	9.3%	18.8%	1.3%

Table 9. Extension for bad illumination

8 tiles, Rayleigh Distribution, Contrast Limit = 0.07, $\alpha = 0.5$.

	Min	Mean	Max	STD
Classification Accuracy	92.0%	93.2%	94.5%	0.4%
True Positive Rate	92.6%	93.0%	93.7%	0.4%
False Positive Rate	4.7%	6.7%	8.4%	1.3%

2.9 Scenic Clues based analysis

The authors have proposed a method which includes three scenic clues: non-rigidmotion, face background consistency and imaging banding effect for accurate and efficient face liveness detection. Non-rigid motion clue indicates the facial motions such as blinking, and a low rank matrix decomposition based image alignment approach is implemented to extract this nonrigid motion. Face-background consistency clue assumes that the motion of face and background has high consistency for fake face images while low consistency for genuine faces, and this consistency can serve as an efficient liveness clue. The authors have implemented GMM based motion detection method for face- background consistency. Image banding effect reflects the imaging quality defects introduced in the fake face reproduction, for which the authors have used wavelet decomposition for detection. The authors have fused these three clues for efficient liveness detection.

2.10 Lip Movement based analysis

The liveness detection approach using lip movement classification and face detection based on face landmarks was introduced by Kollreider . Their work is based liveness detection using face landmarks. The proposed approach analyzes lip movements and lip reading for liveness detection. For classification of lip dynamics, SVM was used by the authors. They proposed an approach to locate the mouth regions and extract OFL in real time. They have used the XM2VTS database on various scenarios. Persons were recorded speaking digits from 0 to 9. The goal was to recognize the digits by lip-motion only. For a digit, they have used 100 short videos. For training (SVM classifier, cross validation), there were a total of 60 videos and for testing, a total of 40 videos were there. For each of digit videos, features vectors are extracted from mouth regions and given to a 10-class SVM. As a result, confusion matrices are obtained. Out of 100 individuals, recognition rate is 0.73 (73%). The authors proposed the method as an indication of liveness.

2.11 Context based analysis

This novel technique of context based face anti-spoofing was introduced by Komulainen . The authors have followed the principle of attack-specific spoofing detection and engage in face spoofing scenarios in which scene information can be exploited. They are trying to detect whether someone is trying to spoof by presenting a fake face in front of the camera in the provided view. The basic idea was that the humans rely mainly on scene and context information during the detection of spoofing; the proposed algorithm tries to impersonate human behaviour and exploits scenic cues for determining whether there a fake face is presented in front of the camera or not. The proposed approach consists of a

cascade of an upper-body (UB) and a spoofing medium (SM) detector which are based on histogram of oriented gradients (HOG) descriptors and linear support vector machines (SVM). The authors suggested that the method can operate either on a single video frame or video sequences. The authors suggested an algorithm to detect close-up fake faces by describing the scenic cues with a cascade of two HOG descriptor based detectors. The alignment of the face and the upper half of the torso were examined using an upper-body detector and using a specific detector that is trained on actual face spoofing examples, the presence of the display medium is determined. To determine the proper alignment of the headand- shoulder region, the upper-body detector that is a component of the human pose estimation pipeline is considered. For experimentation, they have used available CASIA Face Anti-Spoofing Database consisting of several fake face attacks of different natures and under varying conditions and imaging qualities. The proposed approach shows excellent performance the CASIA Face Anti-Spoofing Database showing error rate between 3.3% - 6.8% [27] [28].

2.12 Collection of Regular Methods based investigation

The technique that combines standard techniques in 2D face biometrics was introduced by Kollreider. They have looked into the matter using real-time techniques and applied them to real life spoofing scenarios in an indoor environment. First of all, the algorithm searches for faces and if the face is detected, a timer is started to define the period for collecting evidence. Then evidence is collected for the liveness detection of the faces. For liveness detection, 3D properties or eye-blinking or mouth movements in non-interactive

mode are being analyzed. If no such response is found, responses are asked and checked at random. After the time period expires, verify the liveness of the face. For experimentation, a low cost web-cam that delivered 320x240 pixel frames at 25 fps was employed and computation was done on a standard laptop. The authors suggested that the performance of the proposed method is efficient for the task of public usage.The detect close-up fake faces by describing the scenic cues with a cascade of two HOG descriptor based detectors. The alignment of the face and the upper half of the torso were examined using an upper-body detector and using a specific detector that is trained on actual face spoofing examples, the presence of the display medium is determined [29].

3. DISCUSSION

To determine the proper alignment of the headand- shoulder region, the upper-body detector that is a component of the human pose estimation pipeline is considered. For experimentation, they have used available CASIA Face Anti-Spoofing Database consisting of several fake face attacks of different natures and under varying conditions and imaging qualities. The proposed approach shows excellent performance the CASIA Face Anti-Spoofing Database showing error rate between 3.3% - 6.8%. 2.12 Combination of Standard Techniques based analysis The technique that combines standard techniques in 2D face biometrics was introduced by Kollreider [30]. They have looked into the matter using real-time techniques and applied them to real life spoofing scenarios in an

indoor environment. First of all, the algorithm searches for faces and if the face is detected, a timer is started to define the period for collecting evidence.

Then evidence is collected for the liveness detection of the faces. For liveness detection, 3D properties or eye-blinking or mouth movements in non-interactive mode are being analyzed. If no such response is found, responses are asked and checked at random. After the time period expires, verify the liveness of the face. For experimentation, a low cost web-cam that delivered 320x240 pixel frames at 25 fps was employed and computation was done on a standard laptop. The authors suggested that the performance of the proposed method is efficient for the task of public usage.The analysis might also failed when spoof attacks is performed using more sophisticated methods, just like 3D sculpture face mode.

Table 10. Benefit and Disadvantages of liveness detection formulation

Liveness Indicator/Clue	Advantages	Disadvantages
Texture	1. Easy to implement 2. No need of user collaboration	1. Images with low texture information 2. Dataset must be diverse.
Motion	1. Independent of texture 2. Hard to spoof by 2D image 3. No need of user collaboration	1. Needs video 2. Difficult to use when video has low motion activity 3. Can be spoofed by 3D sculptures
Life Sign	1. Difficult to spoof using 2D image or 3D sculptures 2. Independent of texture	1. User collaboration is needed 2. Depends on face part detection 3. Needs video sequence.

Location of life signs can be of two sorts. Initial one expects specific known cooperation from the client. In the present circumstance the client needs to play out a specific assignment to confirm the liveness of his face picture. This errand can be a sure move that can be considered as a test reaction or a movement secret phrase. Clients who will play out their undertaking accurately are thought to be genuine. The subsequent class doesn't accept any connection from the client, yet centers around specific developments of specific pieces of the face, for example, eye squinting, and will think about those developments as an indication of something going on under the surface and thusly a

genuine face. Life sign based liveness recognition based methodology is exceptionally difficult to parody by 2D face pictures and 3D figures. This approach is additionally free of surfaces yet it might require client joint effort. This approach primarily relies upon face part discovery [31[[32].

4 CONCLUSIONS

This work gave an outline of various methodologies of face liveness location. It introduced an arrangement in view of the kind of methods utilized and sorts of liveness pointer/piece of information utilized for face liveness location which helps understanding different satire assaults situations and their connection to the created arrangements. An audit of most fascinating methodologies for liveness identification was introduced. The most well-known issues that have been seen if there should be an occurrence of numerous liveness discovery strategies are the impacts of enlightenment change, impacts of enhanced clamor on pictures which harms the surface data.

For flickering and development of eyes based liveness recognition techniques, eyes glasses which causes reflection should be considered for future advancement of liveness location arrangements. Moreover, the datasets, which assume a significant part in the presentation of liveness location arrangements, should be educational and various that imitates the normal application situations. Non-intelligent video successions should

incorporate intuitive groupings where the clients play out specific undertakings. Future assault datasets should consider assaults like 3D figure faces and further developed surface data. Our principle point is to give an unmistakable pathway for future improvement of more gotten, easy to use and productive methodologies for face liveness detection.

REFERENCES

[1] Di Wen, Hu Han and Anil K. Jain, "Face Spoof Detection with Image Distortion Analysis" in IEEE Transactions on Information Forensics and Security, 2015.

[2] G. Kim, S. Eum, J. K. Suhr, D. I. Kim, K. R. Park, and J, Kim, Face liveness detection based on texture and frequency analyses, 5th IAPR International Conference on Biometrics (ICB), New Delhi, India. pp. 67-72, March 2012.

[3] Zhenqi Xu, Shan Li, Weihong Deng, "Learning Temporal Features Using LSTM-CNN Architecture for Face Anti-spoofing" in 3rd IAPR Asian Conference on Pattern Recognition, 2015.

[4] G. Kim, S.Eum, J. K. Suhr, D. I. Kim, K. R. Park, and J, Kim, Face liveness detection based on texture and frequency analyses, 5th IAPR International Conference on Biometrics (ICB), New Delhi, India. pp. 67-72, March 2012.

[5] J. Maatta, A. Hadid, M. Pietikainen, Face Spoofing Detection From Single images Using MicroTexture Analysis, Proc. International Joint Conference on Biometrics (UCB 2011), Washington, D.C., USA.

[6] sooyeon Kim, Sunjin Yu, Kwangtaek Kim, Yuseok Ban, Sangyoun Lee, Face liveness detection using variable focusing, Biometrics (ICB), 2013 International Conference on, On page(s): 1 – 6, 2013.

[7] H. K. Jee, S. U. Jung, and J. H. Yoo, Liveness detection for embedded face recognition system, International Journal of Biological and Medical Sciences, vol. 1(4), pp. 235-238, 2006.

[8] Wei Bao, Hong Li, Nan Li, and Wei Jiang, A liveness detection method for face recognition based on optical flow field, In Image Analysis and Signal Processing, 2009, IASP 2009, International Conference on, pages 233 –236, April 2009.

[9] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. "Caffe: Convolutional architecture for fast feature embedding". arXiv preprint arXiv:1408.5093, 2014.

[10] Mahitha M. H, "Face Spoof Detection Using Machine Learning with Colour Features" in International Research Journal of Engineering and Technology (IRJET) Volume 5 Issue 3, 2018.

[11] Anil K. Jain, Patrick Flynn, Arun A. Ross, "Handbook of Biometrics", Springer, 2008. [16] K. Kollreider, H. Fronthaler, M. I. Faraj, and J. Bigun, Real-time face detection and motion analysis with application in "liveness" assessment, IEEE Transactions on Information Forensics and Security, 2(3-2):548–558, 2007.

[12] K. Kollreider, H. Fronthaler, and J. Bigun, Non-intrusive liveness detection by face images, Image and Vision Computing, vol. 27(3), pp. 233-244, 2009.

[13] Jukka Komulainen, Abdenour Hadid, Matti Pietikainen, Context based Face Anti-Spoofing, Biometrics: Theory, Applications and Systems (BTAS), 2013 IEEE Sixth International Conference on Pages: 1-8, 2013.

[14] K. Kollreider, H. Fronthaler, and J. Bigun, Verifying Liveness by Multiple Experts in Face Biometrics, In IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, pages 1-6, 2008.

[15] T. Wang, J. Yang, Z. Lei, S. Liao, and S. Z. Li, Face Liveness Detection Using 3D Structure Recovered from a Single Camera, International Conference on Biometrics, Madrid, Spain, 2013.

[16] Wang S. Y., Yang, S. H., Chen, Y. P. and Huang, J. W. 2017. Face Liveness Detection Based on Skin Blood Flow Analysis, Symmetry, 9(12): 305.

[17] Wang, T., Yang, J., Lei, Z., Liao, S. and Li, S. Z. 2013. Face Liveness Detection Using 3D Structure Recovered from a Single Camera, International Conference on Biometrics, Madrid, Spain. Westeyn, T., Pesti, P., Park, K.H. and Starner, T. 2005. Biometric identification using song-based blink patterns.

[18] Yan,J., Zhang, Z., Lei, Z., Yi, D. and Li, S. Z. 2012. Face liveness detection by exploring multiple scenic clues, 12th International Conference on Control, Automation, Robotics and Vision. Yang, J., Lei, Z., Liao, S. and Li, S.Z. 2013.

[19] Singh, M. & Arora, A. S. 2018. A Novel Face Liveness Detection Algorithm with Multiple Liveness Indicators, Wireless Personal Communications. Socolinsky, D., Selinger, A., and Neuheisel, J. 2003. Face recognition with visible and thermal infrared imagery, Computer Vision and Image Understanding, 72–114.

[20] Sun, L., Pan, G., Wu, Z. and Lao, S. 2007. Blinking-Based Live Face Detection Using Conditional Random Fields, International Conference on ICB, 252-260.

[21] Tan, X., Li, Y., Liu, J. and Jiang, L. 2010. Face liveness detection from a single image with sparse low rank bilinear discriminative model, ECCV.

[22] Tang, Di. et al. 2018. Face Flashing: A Secure Liveness Detection Protocol based on Light Reflection, Network and Distributed Systems Security (NDSS) Symposium, San Diego, CA, USA ISBN 1-1891562-49-5.

[23] Singh, J. and Arora, A.S. 2017. A framework for enhancing the thermographic evaluation on characteristic areas for paranasal sinusitis detection, Infrared Physics & Technology. Singh, M. and Arora, A.S. 2017.

[24] A Robust Anti-Spoofing Technique for Face Liveness Detection with Morphological Operations, Optik-International Journal for Light and Electron.

[25] Ramachandra, R. and Busch, C. 2017. Presentation attack detection methods for face recognition systems: a comprehensive survey, ACM Computing Surveys (CSUR).

[26] Marzec, M., Koprowski, R., Wrobel, Z., Kleszcz, A. and Wilczynski, S. 2015. Automatic method for detection of characteristic areas in thermal face images, Multimedia Tools and Applications, 74(12): 4351-4368.

[27] Lagorio, A., Tistarelli, M. and Marinella Cadoni. 2013. Liveness Detection based on 3D Face Shape Analysis, International Workshop on Biometrics and Forensics (IWBF), : 1-4.

[28] Kim, S., Yu, S., Kim, K., Ban, Y. and Lee, S. 2013. Face liveness detection using variable focusing, International Conference on Biometrics, 1 – 6..

[29] Filipe, S. and Alexandre, L.A. 2013. Thermal infrared face segmentation: A new pose invariant method. 6th Iberian conference on pattern recognition and image analysis. Springer, LNCS, Madeira.

[30] Akbulut, Y., Sengur, A., Budak, U., Ekici, S. 2017. Deep learning based face liveness detection in videos, International Artificial Intelligence and Data Processing Symposium (IDAP), IEEE Xplore DOI: 10.1109/IDAP.2017.8090202.