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Hybrid Classification for Face Spoof Detection

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Abstract: ***ML (machine learning) is consisted of a method of recognizing face. This technique is useful for the attendance system. Two sets are generated for testing and training phases in order to segment the image, to extract the features and develop a dataset. An image is considered as a testing set; the training set is contrasted when it is essential to identify an image. An ensemble classifier is implemented to classify the test images as recognized or non-recognized. The ensemble algorithm fails to acquire higher accuracy as it classifies the data in two classes. Thus, GLCM (Grey Level Co-occurrence Matrix) is projected for analyzing the texture features in order to detect the face. The attendance of the query image is marked after detecting the face. The simulation outcomes revealed the superiority of the projected technique over the traditional methods concerning accuracy.***
Keywords: DWT, GLCM, KNN, Decision Tree

I. INTRODUCTION

Automatic face recognition has pulled much consideration in different access control applications, especially smart phone unlocking due to its user-friendly authorization technology. The emergence of face unlocking function in the Android smartphone operating system has developed face recognition as a new biometric authorization technology for smartphones, just like fingerprint verification (Touch ID) in the iOS framework [1]. Different from fingerprint authorization, there is no need of extra sensor devices in a facial recognition framework. This is due to the fact that all smart phones contain built-in front-facing camera [2]. However, as with other biometric modalities, threats of face spoof attacks on face recognition frameworks must be addressed, especially in unrestricted sensing and non-cooperative subject conditions. Considering the privacy and security of information, how to combat face spoofing attacks has become a major concern for biometric frameworks based on face [3]. Particularly, three major forms of attack include: Photo Attack (e.g., printed photo attack, display photo attack), Replay Video Attack, and 3D Mask Attack. The most common form of spoofing includes Print, display and replay attacks [4]. Many researchers have intensively reviewed these attacks. With the development of the Internet and the increase in information outflow, it is quite easy to get those spoofs, which might be problematic to differentiate visually from the real faces of users. Consequently, reliable face anti-spoofing methods are required to be developed inevitably and deployed in face authentication systems. To deal with face spoofing attacks, the face recognition framework needs a bias to detect whether the face is genuine or spoof. Thus, face spoofing detection is considered as a two-class classification problem and the solution is to learn a classifier that can effectively discriminate between real faces and spoof faces [5].

To deal with face spoofing attacks, the face recognition framework needs a bias to detect whether the face is genuine or spoof. Thus, face spoofing detection is considered as a two-class classification problem and the solution is to learn a classifier that can effectively discriminate between real faces and spoof faces [6]. A general framework of face liveliness detection consists of five steps: image acquisition, face detection, face pre-processing, identifiers' extraction, and face recognition/classification as shown in figure 1.

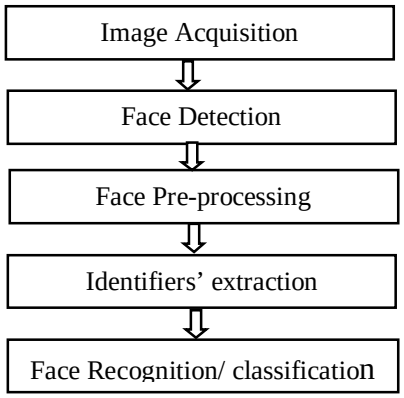


Fig. 1. Face Liveliness Detection Framework

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Image retrieval generally takes place from a still photograph in this step. The objective of this step is to discover some patterns in the photograph with the aim of finding a face. The second step is concerned with verifying the locations and sizes of human faces in random photographs. Face recognition may or may not include face recognition. Face pre-processing is a scheme in which images are cropped to eliminate unwanted parts and, if necessary, image processing (change color space, filtering, etc.) is applied to increase certain parameters to be measured in the next step. The fourth step aims at calculating coefficients or identifying representative values. process. The output of identifiers' extraction stage is reduced dimension, transformation of the data and selection of an appropriate subspace in the original feature space. Once the valid features are extracted, a well-organized and accurate classification model should be designed. Face presentation attack detection is performed by implementing different classifiers. Overall, the monotone classifier model provided with static parameters is likely to diverge the classification results. To get a high level of detection accuracy and generalization potential, different classifiers are used like SVM, KNN, LDA etc. The research community has developed many face spoofing detection algorithms. These algorithms have shown outstanding performance on standard databases. To counter face spoofing attacks, the face recognition system needs a bias to detect whether the face is real or not. There are mainly four categories of face anti-spoofing methods: (1) texture-based methods, (2) motion-based methods, (3) image quality-based methods, (4) depth-based methods.

The purpose of motion-based methods is to detect native responses to living faces, for example, eye blinking, head rotation, and mouth movement. While these methods are competent enough to detect printed photo attacks, they cannot detect replayed video attacks, which offer genuine responses. In addition, these methods need several frames (typically >3 s) to estimate facial movement confined by human physical rhythms. Image Quality Analysis-Based methods are based on capturing the divergence of image quality between live and spoof facial images. Image quality degradation caused by spoofing media (e. g, paper and screen) is commonly seen in spoofing facial images, and printed photos and color space analysis can be used to detect replay videos exhibited on a screen. Hence, these methods differentiate a live face image from a simulated face image by extracting chromatic moment identifiers. These approaches typically use entire photographs to estimate image quality and have great generalization ability. However, image quality can be more discriminatory in mini and localized region of facial photographs. Texture-based methods consider that the application of different spoofing mediums leads to shape distortion and reflection on the surface. It may result in the variation of texture between live and spoofed facial photographs [15]. These approaches extract texture features from one facial to detect face spoofing and can respond quickly. However, when training data is collected from a small number of subjects and under confined scenarios, texture features may not have good generalizability to various facial expressions, posture, and spoofing methods. Therefore, a combination of texture features and image quality features can improve the productivity of face spoof detection. Depth-based mmethods discriminate live 3D faces from spoofing faces presented on 2D planar media by estimating the depth information of a face. The characteristic instances of these methods include defocusing techniques, near-infrared sensors, and light-field cameras. Using Depth features printed photo and video replay attacks can be detected successfully. At the other side, some studies have estimated facial 3D depth information by developing 3D depth analysis techniques. An optical flow field-based approach can analyze the difference in optical flow field between a planar object and a 3D face. Another work uses geometric invariants based on a set of facial landmarks to detect replay assaults. Nevertheless, these techniques typically need a large number of frames or depth measuring equipment to assess the depth information which may increase the system overhead.

II. LITERATURE REVIEW

Haonan Chen, et.al (2019) developed a FARCNN (face anti-spoofing region-based convolutional neural network), on the basis of enhanced Faster RCNN model [16]. Furthermore, an enhanced Retinex based LBP (Local Binary Pattern) was put forward for handling various illumination situations while detecting the face spoofing. At last, the cascading of these detectors was done further. The developed model had generated the optimal outcomes on the benchmark databases. The developed model was evaluated in the experimentation with regard to the generalization capacity. The experimental outcomes confirmed that the developed model was efficient. A technique to detect the face spoofing was investigated by Graham Desmon Simanjuntak, et.al (2019) on the basis of analyzing the color distortion to capture the chromatic aberration from a face image [17]. The color distortion was analyzed for extracting the color moment and ranked histogram attributes so that 116 feature vectors were produced. Thereafter, the PCA (Principal Component Analysis) algorithm employed feature vector for mitigating the dimensionality. The face images were classified as live or spoof using NB (Naïve Bayes) classification on the principal components. The experimental results depicted that the investigated technique performed well in comparison with the traditional technique and yielded higher TPR (True Positive Rate) up to 97.4%. A technique recognized as FCN-DA-LSA (Fully Convolutional Network with Domain Adaptation and Lossless Size Adaptation) was introduced by Wenyun Sun, et.al (2020) to detect the face spoofing [18].

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The basic properties of distorting the face spoofing were exploited in the FNC algorithm. The DA layer was considered for enhancing the generalization over diverse domains. The LSA was assisted in preserving high-frequent spoof clues occurred due to the face recapture procedure. The introduced technique performed more effectively in contrast to existing techniques. An innovative attribute called SBP-TOP was suggested by Ying Zhang, et.al (2018) for recognizing the face spoofing in effective manner [19]. This approach provided texture information for the face region taken from spatial and temporal viewpoints. The MSU MFSD (Michigan State University mobile face spoofing database) and CASIA were utilized for testing the suggested attribute. The results demonstrated that the suggested attribute provided the accuracy around 95% on the generated datasets and was more effective in comparison with other techniques. A fast and robust algorithm was designed by Theja J. Jayan, et.al (2018) for detecting the fake faces from images obtained from the online social networks [20]. This algorithm was deployed for extracting face segments in diverse color spaces and estimating the illuminate map of the region. Furthermore, this algorithm was adopted for computing the metrics of image quality of segment and comparing them with the background region. The spoof faces were identified using QDA (Quadratic Discriminant Analyzer). The DSO-1 and DSI-1 datasets were utilized to test the designed algorithm. The results revealed that the accuracy obtained from the designed algorithm was calculated 96.5% to detect the face spoofing. A method to detect the face spoof was established by Mayank Yadav, et.al (2018) for classifying the faces as spoofed or real from images [21]. The textual attributes available in a test image were analyzed using DWT (Discrete Wavelet Transform) algorithm. The SVM (Support Vector Machine) was adopted in earlier approach for classifying the attributes as spoofed or normal. Hence, there was a necessity of improving the accuracy of the presented approach for detecting the spoofed faces. A comparative analysis was performed for analyzing the established method with respect to accuracy and execution time. A NN (neural network)-based face anti-spoofing algorithm was projected by Xiaojun Wu, et.al (2021) in which DP (dual pixel) sensor images [22]. Initially, a DP image pair was utilized for input in network and a depth map was created with a baseline. Subsequently, real individuals and planar attack shapes were differentiated by training the classification network so that a binary output was generated. The experimental results exhibited that the created depth map assisted in distinguishing the real human faces from non-face attack such as images recaptured from photos or screens. The supremacy of the projected algorithm was proved over traditional techniques. Gusi Te, et.al (2020) focused on performing 3D face anti-spoofing with the implementation of HGCNN (Hypergraph Convolutional Neural Networks) [23]. At first, a computation-efficient and posture-invariant face representation was developed using some key points on hypergraphs. The implemented algorithm employed hypergraph representation along with hypergraph convolution in order to extract the attributes. Moreover, the implemented algorithm was determined on a three-dimensional face attack data set and the limitations of this dataset were tackled. The experiments outcomes indicated that the implemented technique was applicable. An effective mechanism was recommended by Gustavo Botelho de Souza, et.al (2018) in order to detect the face spoofing on the basis of wCNN (width-extended Covolutional Neural Network) [24]. The training of every part of wCNN was done in a given region of the face. After that, the face presented to the sensor was classified as real or fake by integrating their outputs. This mechanism was deployed for learning deep local attributes from each facial area as it had width-wide architecture. The results proved that the recommended mechanism more adaptable as compared to other techniques with regard to hardware resources and processing time. A novel anti-spoofing network model was intended by Aleksandr Parkin, et.al (2019) in which the data related to multi-modal image was utilized and intra-channel attributes were aggregated at multiple network layers [25]. The face was recognized by transmitting strong facial attributes and these attributes were useful to detect the spoofing attacks. In the end, an ensemble of models was implemented for expanding the generalization potential of the intended technique to unseen attacks. The training of these models was done for dealing with diverse spoofing attacks. The results acquired on CASIA-SURF revealed that the intended model had generated optimal outcomes. A geometric technique was formulated by Alexander Naitsat, et.al (2018) in order to detect spoofing attacks in face recognition-based authentication systems [26]. The formulated technique was planned on the basis of projective invariant relationships which were not relied on the camera metrics and lighting conditions. A comparative analysis confirmed that the formulated technique performed more accurately and automatically. A constructive technique was suggested by Arnav Anand, et.al (2020) for detecting the face anti-spoofing for which CNN (Convolution Neural Network) and LBP (Local Binary Pattern) models were employed [27]. At first, diverse attributes were extracted using CNN and the texture attributes were extracted with the help of LBP. Thereafter, SVM (Support Vector Machine) was applied to determine that the face was authentic or spoofed in the classification. The retrieval of two diverse lists of probabilities was done from both the models with dissimilar attributes. These probabilities were fused together for detecting the authentic faces from spoofed faces. A countermeasure capable of detecting the unauthorized access attempts in facial recognition systems was developed by Raphael Ruschel, et.al (2019) [28]. Various researchers deployed only face foe detecting the facial spoofing attacks. A DL (deep learning) technique, in which the entire frame was utilized, adopted in this approach with the objective of detecting the PAs (presentation attacks).

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The experimental results revealed that the developed approach with GoogLeNet architecture assisted in detecting various attacks. A new method was introduced by Neenu Daniel, et.al (2019) for analyzing robustness of the system utilized to detect the face spoofing for which entropy-based texture attributes were integrated with quality attributes [29]. A public dataset was applied for quantifying the introduced method. The experimental results depicted that the introduced method was efficient to recognize several face spoofing attacks and provided the accuracy up to 98.2% in comparison with traditional methods.

III. RESEARCH METHODOLOGY

This research work is conducted to classify the face for which the KNN (K-Nearest Neighbour) algorithm is deployed. This algorithm makes the implementation of several n-dimensional numeric attributes for defining the training samples. A minimal point is denoted with a sample present in n-D pattern space. After that, the sorting of a part which is of enormous size is done in n-dimensional pattern space among the training samples. When the sample is not known, the KNN algorithm is adopted for determining whether the sample is closer training sample and to explore the pattern space. ED (Euclidean distance) is utilized to verify the similarity of the unknown sample with the training sample. A break and weight are allocated to each feature through KNN instead of implementing BP (back propagation) and DT (decision tree). The confusion is occurred when several attributes are present. The projected algorithm is adopted for the unknown sample in order to obtain the prediction. This algorithm is useful for providing average value for this case. The value generated by the unknown sample associated with the K-Nearest Neighbour (KNNs). Therefore, the projected algorithm proved more effective in contrast to other ML (machine learning) algorithms. The DSW (Discrete Wavelet Transform) is deployed for the analysis of attributes of testing image. The KNN algorithm is fed with detected attributes so that the face is classified. Therefore, KNN is called a non-parametric supervised learning algorithm. The feature space is consisted of nearer training samples which are considered in the classification. The training process concentrated on sorting the feature vectors along with the labels of training images. The classification procedure is executed to distribute the unlabelled question point for the label of its K-Nearest Neighbour. The labels assigned to KNN are utilized to characterize the object. For this, majority share cote is employed. The object is a class of an object available closer to it in case k=1. k is taken as an odd integer in the presence of only 2 classes. The KNN emphasized on classifying the samples in accordance with the majority class of its NN (nearest neighbour).

$$Class = arg_v max \sum_{(x_i, y_i) \in D_z} I(v = y_i) \qquad (1)$$

In which, v defines the class label. y_i is the class label for ith nearest neighbours. The I is an indicator function which provides the value 1 in case the argument is true, otherwise the value is 0. Therefore, the major intend of KNN is to assign the samples. Three components such as a set of labelled objects, a distance or similarity metric are included in the K-Nearest Neighbour algorithm for evaluating the distance from the objects to the number of NNs. The recognition task becomes effective by choosing a suitable similarity function and value. Therefore, the KNN is proved as a simple algorithm. The deployment and analysis of this algorithm is an easy task.

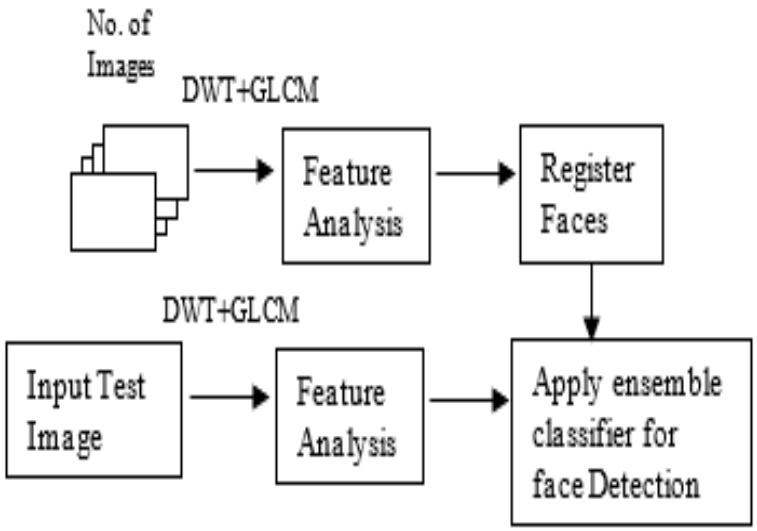


Fig. 2. Research Methodology

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IV. RESULT AND DISCUSSION

The core of this research work is face spoofing recognition. This work applies GLCM algorithm for extracting features. The classification is performed using an Ensemble Classifier. Face recognition is performed using Six facial images of different persons. These images are given as input to the recognition framework. Table 1 features these images.

Table I. Input Images



Many texture features of these photographs are computed for face recognition. The most used characteristics are contrast, uniformity, correlation, and entropy. Table 2 features different values of these attributes:

Table II. Values of facial pictures

Image Number	Contrast	Homogeneity	Correlation	Entropy
Image 1	0.92	0.891	1.2	2.56
Image 2	0.90	0.901	1.8	2.90
Image 3	0.89	0.905	1.6	2.78
Image 4	0.93	0.862	1.4	2.65
Image 5	0.92	0.910	1.3	2.12
Image 6	0.91	0.815	1.4	2.15

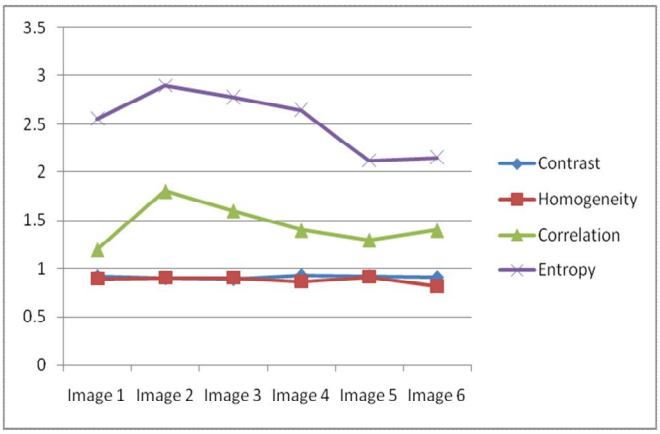


Fig. 3. Feature of six facial pictures

Image retrieval generally takes place from a still photograph in this step. The objective of this step is to discover some patterns in the photograph with the aim of finding a face.

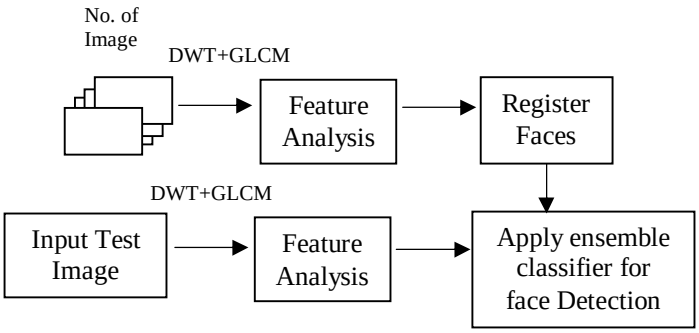
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To test the developed methodology, this work considers three universal metrics namely precision, recall and accuracy. These metrics have been explained as follow:

1) *Accuracy:* Accuracy is defined as the correctly classified number of points divided by the total number of points multiplied by 100. Accuracy = (Number of points correctly classified)/ (Total Number of points) *100
2) *Precision:* It is defined as the positive predictive value and can be calculated as the proportion of applicable cases among the retrieved cases. Precision= (True Positive)/ (True Positive+False Positive)
3) *Recall:* It is defined as the proportion of relevant cases whose extraction is performed on the total sum of applicable cases. Recall= (True Positive)/ (True Positive+False Negative)

Table III. Performance Analysis

Parameter	KNN Classifier	Ensemble+GLCM
Accuracy	84.56 percent	92.34 percent
Precision	83.45 percent	93.45 percent
Recall	81.90 percent	92.65 percent



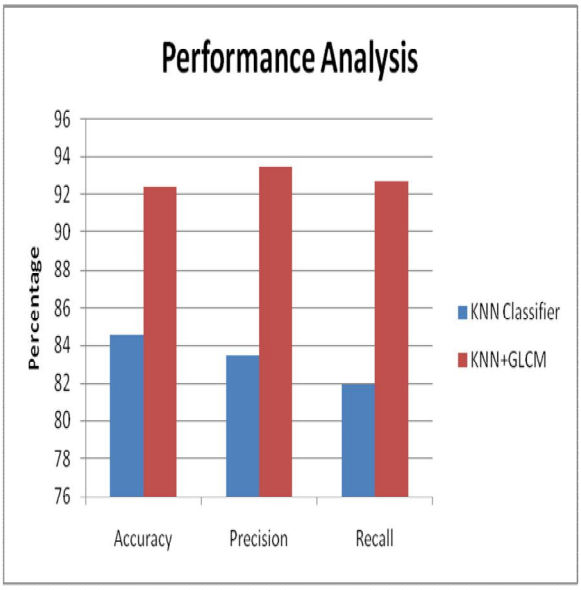


Fig. 4. Performance Analysis

Figure 4 shows the precision, recall, and accuracy-based performance analysis of the KNN (K-Nearest Neighbor) classifier and the Ensemble classifier +GLCM. It is clear from the figure that the Ensemble classifier + GLCM algorithm performs better than KNN in terms of all three metrics.

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V. CONCLUSION

Facial recognition is an elementary part of ML (Machine Learning). The ML algorithm aims to extract representative values based on past understandings. Different processes such as segmentation, identifier analysis, and classification etc. are performed using a training set. Image is captured as a test set. The image is supposed to identify for the authorization framework. This research work uses ensemble to classify faces. GLCM (Gray Level Co-occurrence Matrix) is adopted as a statistical method of texture feature analysis. The results of Simulation conform the competency of the proposed methodology of facial recognition. The proposed model improve results upto 8 percent as compared to existing research for face spoof detection. The proposed model can be further improved using transform leaning in future.

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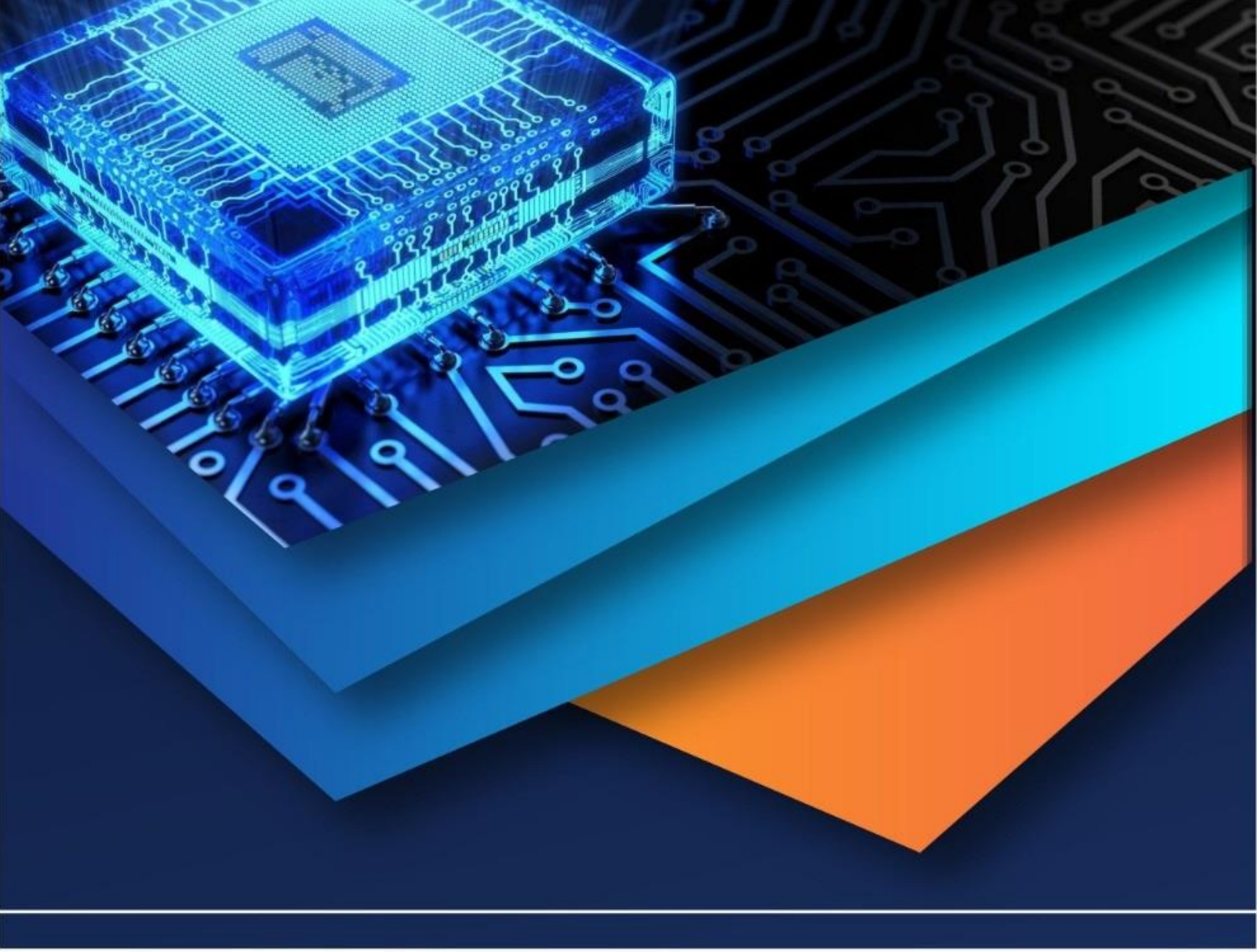
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