iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 Issue: XII Month of publication: December 2021

DOI: https://doi.org/10.22214/ijraset.2021.39245

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XII Dec 2021- Available at www.ijraset.com

Study of Ear Biometrics Based Identification System Using Machine Learning

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Abstract: Within the biometric industry, computerized person identification using ear pictures is a hot topic. The ear, like other biometrics like the face, iris, and fingerprints, contains a huge number of particular and unique traits that may be used to identify a person. Due to the mask-wearing scenario, most face detection methods fail in this present international COVID-19 pandemic. The eardrum is a great data source for inactive person authentication since it doesn't necessitate the person we're attempting to pinpoint to cooperate, and the structure of the ear doesn't change significantly over time.. The acquisition of a human ear is also simple because the ear is apparent even while wearing a mask. An ear biometric system can enhance other biometric technology in an automated person identification system by giving authentication cues when other information is unreliable or even missing. We provide a six-layer deep convolutional architecture for ear identification in this paper. On the IITD ear dataset, the deep network's potential efficiency is assessed. The IITD has a detection performance of 97.36 percent for the deep network model and 96.99 percent for the IITD. When paired with a competent surveillance system, this approach can be beneficial in identifying people in a large crowd.
Keywords: Biometrics, Person identification, IIT-D, Deep learning, Ear dataset

I. INTRODUCTION

We need to show that utilising the ear as the base for a new category of biometrics is feasible. We can't prove that every person has a fully unique pair of ears in the same way that no one can establish that fingerprints are unique. Instead, we may remark that this is probable and back it up with evidence from two Iannarelli investigations [1]. The first examines over 10,000 ears from a randomly selected location in California, while the second examines tested twin and sister twins with genetic factors that are regarded equal. Both studies reinforce the idea that the ear possesses precise physiological features, keep in mind that in both trials, all of the ears tested were shown to be distinctive, even though the twins were shown to be similar. The next stage is to investigate if the ear can offer fingerprints that are constant over time after exhibiting distinctiveness. The ear's structure does not appear to vary significantly over time. According to medical study [1,] ear growth after the first four days of pregnancy is proportionate. Despite the fact that ear boom is proportionate, gravity appears to be capable of vertically growing the ear. The ear lobe is the most affected by this lengthening, and measures reveal that the exchange is non-linear. The rate of elongation is around five times higher than usual from of the age of 4 months to the age of eight, after which it remains constant until around the age of 70, when it accelerates again. The ear fingerprints are plausible in the sense that ear construction is expected to be specific to each person and that features field measurements of that morphology are consistent across time. Ear biometrics authentication is fascinating if they are feasible since it is considerably more inactive than face detection, rather than challenging to separate face biometrics, robust such as certain extracted fingerprint scanners like those in fingerprints might be used.

A. Iannarelli's Ear Biometrics

Iannarelli [1] came up with an anthropometric recognition approach based on ear biometrics. Figure 1.1 shows the twelve estimations that make up the "Iannarelli System" (b). The coordinates shown were determined using aligned and normalised photographs of the proper ear. To normalise and align the images, they are shown onto a traditional "Iannarelli Inscribed" extending easel that is adjusted horizontally and vertically until the ear image falls into a present location on the easel. The mechanism, according to Iannarelli, needs careful positioning and levelling of the ear pox: After the ear is fixed and the image is limited within the easel boundaries, set the easel such that the indirectly guiding line is parallel to the outer strong spot of the tragus flesh line. The tragus's tip should be just touching the direct line. (For the 5 white lines in the left ear biometrics, see Figure 1.1(a).) Start moving the accessory gently until the top section of the oblique booklet line intersects with the point on the ear photo in which the internal helix rim surface shapes the top cucaracha flesh line underneath the depression or hollow known as the rectangle fossa, while preserving the ambiguous line touching the tragus.

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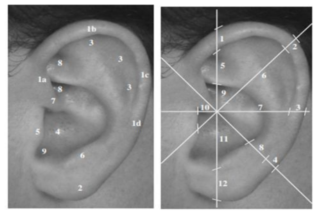
When the indirectly guideline was utilised to align the ear shot, the ear photo was carefully synchronised. The size of the ear image must now be adjusted by the professionals. The ear picture is stretched or shrunk to its suitable size for comparison and classification using the easel's short vertical rule (the right white line in Figure 1). 83-84] 83-84] [1, pp. 83-84]



(a) Anatomy. (b) Measurements.

Figure 1.Ear Biometrics: (a) 1 Helix Rim, 2 Lobule, 3 Antihelix, 4 Concha, 5 Tragus, 6 Antitragus, 7 Crus of Helix, 8 Triangular Fossa, 9 IncisureIntertragica. (b) The locations of the anthropometric measurements used in the “Iannarelli System”

The final photos are standardised because each ear is matched and scaled during the design process, allowing for the retrieval of similar measurements from the pix all at once. The length between each of the named parts in Figure 1.(a) is considered in three devices and given an integer value. These twelve factors, as well as data on cohabitation and race, are then used to identify the person. Because an issue is classified into a single point in a 12 dimensional numeric space, where each unit on an axis represents a 3 mm height difference, inside each relationship and race group, the system allows for a too small class region, as previously stated. Using the 12 measures, presuming a four-unit average variability within the group 6, Burge and Burger get a space with less than 17 million great points (i.e., 12 mm). Though there are simple ways for raising the scale of the length (e.g., adding more measurements or adopting a smaller metric), the technique is inadequate for system vision owing to the difficulties in detecting the anatomical point that serves as the size gadget's starting point. Because all future variables are measured in respect to this origin, if it is not exactly determined, all subsequent measurements will be incorrect. On site page 83, Iannarelli states, "This is step one in synchronising the ear image....," indicating that he was aware of the problem. And it must be accurate; else, the entire kind of the ear may be erroneous."

II. OBJECTIVES

1) To look into existing Ear Biometrics approaches for selecting various dataset properties.
2) Create a deep learning model for an ear biometric data detection algorithm using the gathered dataset.
3) Against contrast a machine-learning-based ear biometrics system to a standard ear biometrics-based identification system.
4) The examination made use of both conventional and self-created data sets.

III. LITERATURE REVIEW

The notion of skin reflection within the safe range of the EM (Electromagnetic) part of the electromagnetic spectrum was used by Aakanksha and Setia, H, in their recommended painting [6], due to the fact that the skin has a 54 percent mirrored image and the fats under the skin have an 8 % reflected image. It was suggested that an ear imaging mechanism be used, as well as adequate monitoring of light reflected to use a photometer. Following that, the reflected spectrum is standardized, and the identical spectra are used to paint every ear separately. Codes and techniques for programming the spectrometer and determining the cutoff cost based on the most allowable error were demonstrated. How can the attractiveness correctness be changed indirectly when light reflection differs from ear to ear and each person's pores, skin, and fat intake is unique? In 2012, P. Ramesh Kumar et al. introduced the pixel-based feature identification technique [7] for the Ear biometric model. Offering a strategy based on ear shape photo pixels invites researchers to focus on ear identity verification since pixels are the essential components of an image.

In 2017, Mozammel Chowdhury et al. proposed an ear biometric attractiveness strategy based on the local capabilities of the human ear and a neural network algorithm [14]. The approach extracts the edge features from the recognized ear after guessing the position of the ear from the facial picture. They were chosen since portion local functions are unaffected by strobing lights and obstruction. By matching the user's collected ear functions to a feature database, a neural network is used to understand the client. The robustness and efficacy of the proposed strategy are excellent, but there is still potential for development. . In 2018, Salman Mohammed Jidda and colleagues [15] released research that employed textural and geometric skills to enhance ear identification. The AMI ear database was utilized in this study to try recovering Local Binary Patterns abilities and using the Laplacian filter on

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raw pictures one at a time to extract architectural skills. In order to find the region of intense interest in human ear photos, the ear database was analyzed by dividing ear images into four quarters and experimenting on each one independently. The textural and geometric variables were then fused, and tests were run to verify the contribution of the fused capability. While the top left zone ear image accuracy was finished, the upper left ear pictures with the Laplacian filter had a substantially lower average accuracy of 51.8 percent, which needed to be improved.

IV. METHODOLOGY

A sensor in an ear biometric device is frequently used to acquire the ear image (camera). The system does image pretreatment and feature extraction, as well as identifying features that may be utilized to distinguish between ear pictures. These features are stored in a feature database. During testing, the attributes produced from the test image are matched to those in the database. Finally, the classifier chooses from the database the best relevant ear image. Three main steps may be identified in a general ear biometric system, as shown in Fig.2. The three phases are preprocessing, feature extraction, and classification. Preprocessing and feature extraction are used in both the training and testing phases. This section examines the three phases as well as the major algorithms used in each.

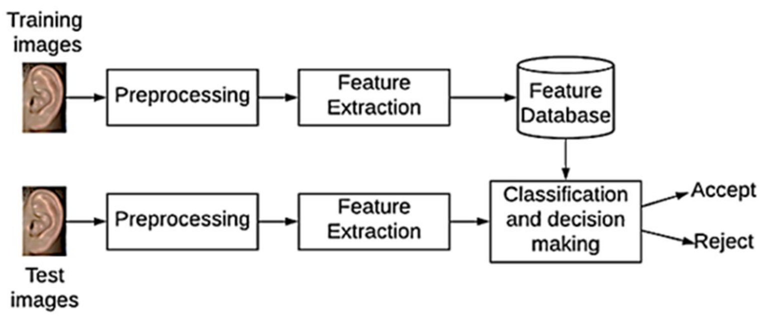

Fig.2. General Block diagram of an ear biometric system

A. Preprocessing

Prior to processing, preprocessing is necessary to transform the photographs to a standard and suitable format. Data preparation ensures that the image's most important attributes are enhanced while unwanted data such as noise is removed. The two primary types of preprocessing approaches are filter-based and vividness processes.

1) *Filter-based approach:* Filters are commonly used to reduce noise and emphasize important features such as edges, as well as to smooth the image. Fuzzy filters use fuzzy control logic to reduce noise [22]. Mean and median filters use a kernel to calculate the mean or median value of a pixel's neighbors, including yours, to see if it represents its surroundings in a picture [24, 25]. The Gaussian filter is similar to the mean filter, but it uses a Gaussian kernel to minimize noise [25, 27]. Gabor filters are commonly used to extract both frequency and spatial data from images [26]. Its Log Gabor Filters variant is used to get around the bandwidth limits of Gabor filters [27]..
2) *Intensity-based approach:* In general, colored images do not convey all of the data needed to identify edges and features. It's often tough to interpret intensity changes in a colorful image. As a consequence, a three-channel (RGB) image is limited to a single (grayscale) image using RGB to grayscale converter to minimize complication [10, 24]. Another intensity-based approach is statistical redistribution, in which the image's intensity is scattered throughout a histogram and the image's global contrast is raised [28].

B. Feature Extraction

Simply put, feature extraction is the process of determining the main characteristics of a photograph that enable it to be recognized. The goal of feature extraction is to reduce dimensionality by using a small number of features to describe the entire image. The aspects of a photograph that can be used to features extracted are listed below.:

- *Color:* The value of a pixel that allows it to be distinguished from other pixels. Shape refers to the measured data about the items in a photograph.
- *Texture:* Is the information concerning the crassness or regularity of a picture.

Many scholars have contributed minutiae extraction algorithms based on the foregoing qualities from the geographical and magically morph realms of image processing.

1) *Geometric-based Techniques:* The helix, tragus, antihelix, and concha are all unique ear form features. Angular shapes techniques are used to extract these shape-based properties. The strategies listed below are some of the most prevalent ways to do this.:

a) *Canny edge detection*: The edges of the ear picture are located using this procedure. A Gaussian filter is used to reduce noise. The slope is then calculated using any gradient operator, such as Sobel, Roberts, or Prewitt. Pixels that exceed a specified limit are selected and preserved as edge elements. These segments' boundaries are then stitched together to form unbroken segments [22, 29].

b) *Contours of ear images*: Several geometrical properties of the ear are identified using the ear contour. Only a few of these features are the curve start and finish locations, curve path points, and the gradient of the line between the start and end points of the contour. They're employed to create the feature database that may be used to verify the ears' authenticity [10].

c) *Statistical feature based method:* Ear image statistics such as ear height, ear width, and angles produced here between external borders of the ear and the half of the line forming the ear's height are included in this method's feature database [11, 30]..

2) *Appearance based techniques*: Using image techniques loudness and roughness, feature data is retrieved. These algorithms employ shape features and matrix factorization techniques to extract individual ear features. The specifics are as follows:

a) *Feature descriptors:* A feature extraction module is a method that returns an image as its input and outputs a feature vector. Local Binary Patterns (LBP) and Local Phase Quantization (LPQ) are the most extensively used pattern identifiers for storing local texture data in the spatial and spectral [20,21,31]. The Histogram of Oriented Gradients (HOG) is another classification method that counts the occurrences of distinct gradient directions within a small region of an image [21, 24, 31, and 33]. Binarized Statistical Images Features (BSIF) [20, 21, 31], Patterns of Oriented Edge Magnitudes (POEM) [21], and Scale-Invariant Feature Transform (SIFT) [32] are other possible feature descriptors used in ear biometrics.

b) *Dimensionality Reduction Techniques:* PCA [21, 24, and 34] is a matrix factorization technique that takes a higher-dimensional feature map and projects it to a lesser input vector while preserving its unique properties. Linear Discriminant Analysis (LDA), which emphasizes on preserving class-discriminatory information, is another method for image compression [31]. Reduced-dimensionality approaches are typically used with other methods, such as local features.

c) *Force Field Transformations*: It's an intensity-based approach that treats each pixel in the image as a source of force fields. Each pixel generates a symmetrical circular force field. They help to reduce energy wells, lines, and routes by using the energy properties of the ear image. The noise sensitivity of this approach is great [15].

d) *Wavelets-based techniques:* Haar wavelets are one of the most well-known and fundamental wavelets. The textural features of the ear are extracted using the Wavelet packet transform. The feature vectors are then constructed by quantizing the wavelet. Because of its inherent property of robust image fragmentation and rebuilding, this technique is beneficial in the field of biometrics [16, 17 and 37]..

C. Classification and Authentication

After feature extraction and classification vector construction, the program must compare the characteristics of the test picture to the elements in the database. Finally, the picture has been validated. The below are some of the several methods for doing so:

1) *Neural Networks:* A neural network is trained to learn and accomplish a problem using numerous nodes and layers. Using the multiple extracted parameters, the neural network is trained. The number of nodes in the input vectors determines the dimension of the feature vector. A rating value represents the degree of similarity between the attributes of the test picture and those in the library. If the score falls below a particular threshold, the ear image is not confirmed [22].

2) *Normalized Cross Correlation (NCC):*. NCC is used to evaluate the relation between different signals or images. It's used to evaluate the database picture's component designs to the test image's purpose of improvement. Similar to neural networks [28], a limit is used to assess if the test picture fits the one in the database.

3) *Support Vector Machines (SVM):* SVM is a classifier that tries to distinguish two groups using an ideal hyperplanes. It is a technique includes since it works well even with noisy images. The ear parameters are trained using the SVM classifier, and thresholding is done during making decision by selecting appropriate bias and weight values [35, 36].

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4) *K-Nearest Neighbors (KNN):* KNN uses Euclidean proximity to measure the position seen between vectors of the test and the train image. The KNN approach assigns a class to a testing picture based on the ruling group of the test image's 'k' closest feature space peers [33, 38].
5) *Minimum Distance Classifier:* In a multi-feature space, the minimum hop adoption of data the test picture to the class with the highest match, i.e. the class with the smallest route. The distance is a measure of likeness in which the shortest route represents the greatest resemblance [37].

V.RESULTS AND OBSERVATIONS

Based on the above discussion, our methodology will comprise three steps:

1) Data-Set Collection
2) General Procedure
3) Evaluation Procedure

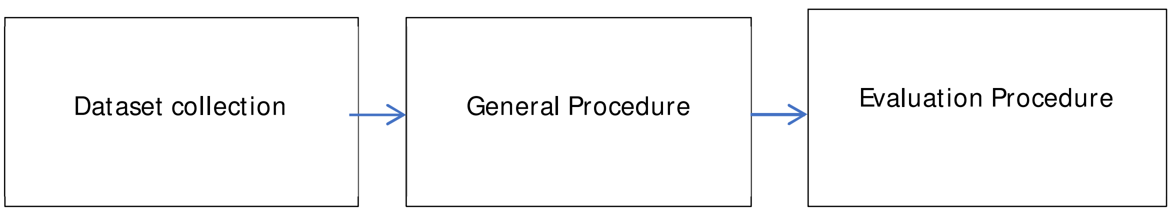

Fig. 3: Block diagram of methodology

A. *Data-Set Collection*:

We'll use the consistently identifies IITD, that is used by the overwhelming bulk of researchers in this area, as well as create our unique dataset by collecting ear images from some of our agency's pupils..

B. *General Procedure of Proposed Technique*

The method for biometrics will be carried out in three steps:

1) The Discreet Wavelet Transform (DWT) will be used since it offers the following pre-processing: When contrasted to other pre-processing methods, this technique yields better results.
2) Feature Extraction: For feature extraction, we will utilise the PCA matrix factorization technique, which is computationally efficient and yields excellent results.
3) Classification algorithm: For classification, we'll utilise the KNN Classifier, which outperforms other. classification techniques and is very scalable

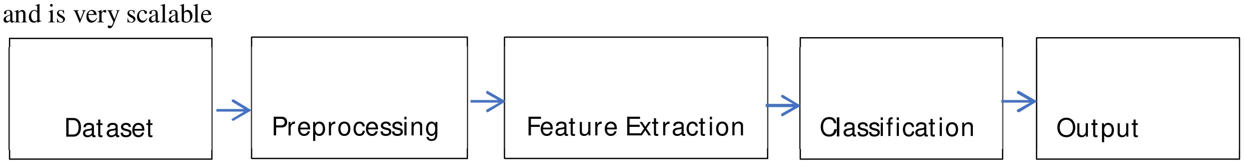

Fig.4: Block diagram of general procedure

C. *Evaluation Procedure*

The following parameters will be taken into account throughout the evaluation:

1) *Accuracy:* The ear biometric system must be able to reliably validate a person's identity based on a photograph of their ear. Reliability is a statistic that measures how often the system identifies items properly. The system's dependability should always be improved. Other name for it is categorization performance [40].
2) *False Acceptance Rate (FAR):* The risk of a biometric system incorrectly approving an illegal user's access effort is measured by the incorrect enrollment. [40] The FAR must be kept to a basic essential.
3) *False Rejection Rate (FRR):* The false removal efficiency determines the likelihood of a biometric system refusing an allowed user's access attempt by mistake. [40] The FRR should be kept to a minimum.

4) Samples

Figure 5 Sample figure 1

Figure 6 Sample figure 2

Figure 7 Sample figure 3

Figure 8 Sample figure 4

We will use these parameters to compare with the already existing ear biometrics technique.

Table 1 Performance matrix

Decision threshold	Recall TRP	Precision	FAR	FFR
0.961	0.91	0.70	0.11	0.11
0.962	0.98	0.71	0.12	0.11
0.963	0.88	0.76	0.14	0.12
0.964	0.81	0.75	0.10	0.10

The results of the experiments reveal some intriguing details insight into the underlying geometric properties of the ear. The common challenges observed during feature extraction and subsequent derivation of inter feature mathematical hash values from the tests opened up new opportunities for future research in this sector. Common metrics were used to validate the facial similarity predictions. Table I lists the system's performance metrics derived from the numerous simulations.

The threshold values are based on a Bayesian comparison of two pictures of ears. The False positive rate (FAR) and False rejection rate (FRR) drop when the threshold is raised, but the Recall or True positive rate (TPR) begins to fall. As can be seen, the average degree of connection between two images of the same topic is around 0.96. Meanwhile, images with varied topics have an average score of 0.85 to 0.93. Because the human side profile changes only little, comparing side faces using geometric computations needs a high degree of accuracy (considering the experimental setup)

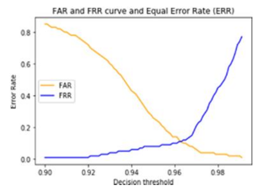

Figure 9 The FAR and FRR cyrve meet at 0.11 and EER is 0.98

VI. CONCLUSION

In this study, we developed a simple deep CNN architecture for recognising people from ear images. Classical computer vision systems use hand-crafted features, but CNNs learn the features from the input image right away, resulting in better performance. We explored the potential efficiency of the built Deep CNN on the IITD-II Ear dataset by modifying factors such as kernel size, learning rate, epochs, and activated functions, and we achieved a 97.36 overall accuracy. In both a controlled and uncontrolled context, the Deep CNN is evaluated against the AMI ear dataset, and it obtains a respectable recognition rate. Because the model requires extremely minimal RAM, it may be transformed into any embedded/handheld device. When this model is combined with an adequate monitoring program, automatic human recognition in densely crowded areas such as malls, railway stations, and banks is possible

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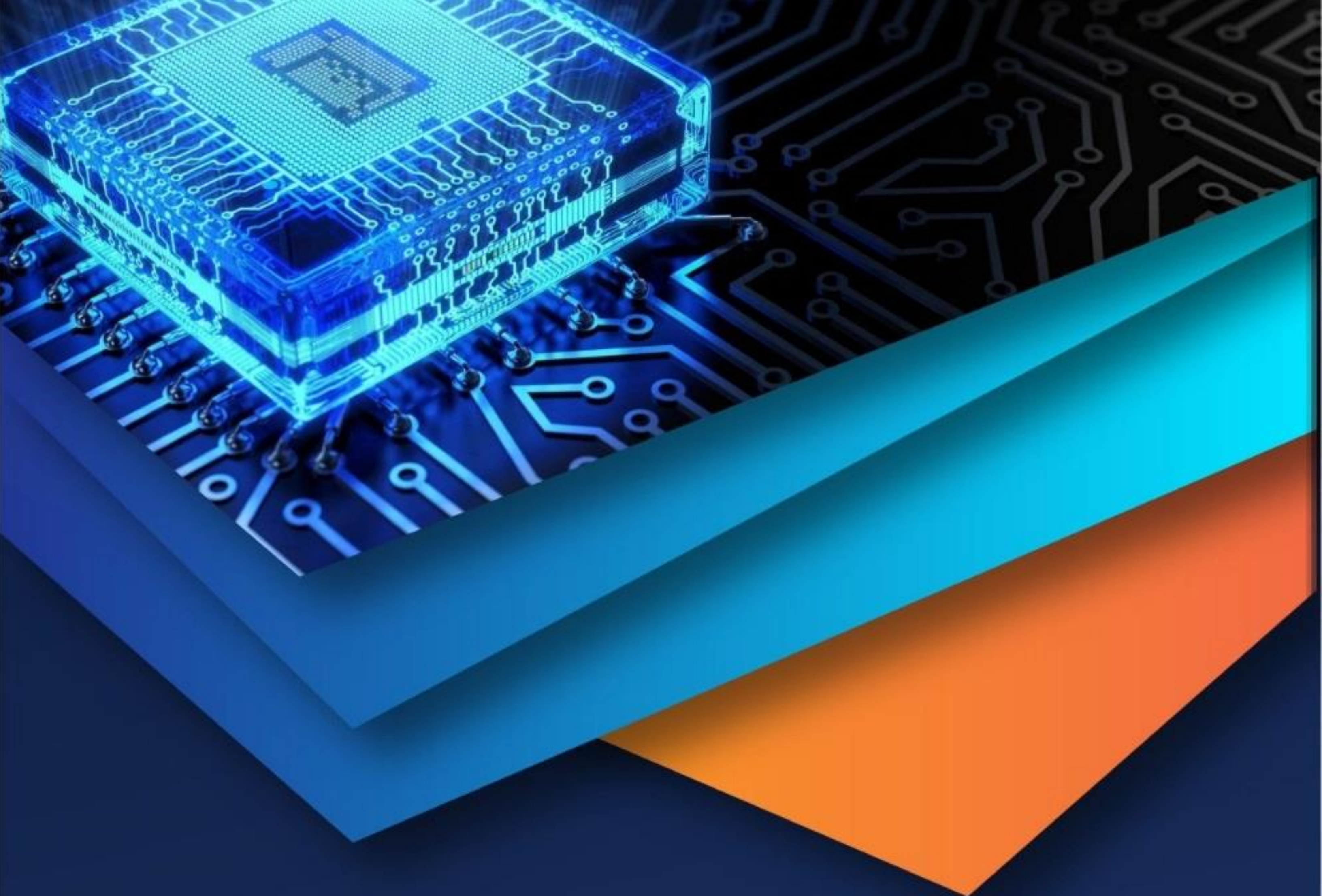

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