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Physiological Measure of Drowsiness Using Image Processing Technique

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Abstract— Every year, most of the accidents occur due to drowsiness of drivers which cause severe casualties. Drowsiness reduces the perception level and decision making capability of the driver which negatively affect the ability of the driver to control the vehicle. Proper attention must be paid towards reducing the accidents that occur due to driver drowsiness. Monitoring driver behavior is one of the best ways to prevent fatal accidents. Proposed model detects drowsiness condition of driver by analyzing his eye blink rate and yawning state. The shape and appearance feature to detect eye blink and yawning state is extracted using Histogram of Oriented Gradient (HOG) feature from detected face. Linear Support Vector Machine (SVM) is employed for classification in two stages. In the first stage, classifier is employed for eye blink detection and in the second stage the classifier is employed for yawning detection. The proposed work is implemented using MATLAB 2015a and detection rate was found to be 93%. The use of HOG feature for drowsiness detection makes the system robust to age, gender, small pose variations and real time implementation is made much easier.

Keywords— Drowsiness Detection, Histogram of Oriented Gradients (HOG), Support Vector Machines (SVM).

I. INTRODUCTION

All over the world and every day, driver's fatigue and drowsiness have caused many accidents. In fact, drowsiness is the case of about 20% of all accidents in the world [1, 2]. As a result, an electronic device to control the driver's awareness is needed. This device should monitor and detect the driver's drowsiness online and activate an alarm system immediately. Fatigue, sleepiness and drowsiness are often used synonymously. Fatigue and sleep are contributing factors in thousands of crashes, injuries and fatalities annually. Several researchers have reviewed technological devices for the detection and countering of driver fatigue. Driver fatigue can be subcategorized into sleep-related (SR) and task related (TR) fatigue based on the causal factors contributing to the fatigued state [2]. Sleep deprivation, extended duration of wakefulness and time of day (circadian rhythm effect) affect SR fatigue. Certain characteristics of driving, like task demand and duration, can produce TR fatigue in the absence of any sleep-related cause. SR fatigue is also influenced by homeostatic factors, such as the duration of wakefulness and sleep deprivation. Performance becomes worse the longer a person remains awake. Sleep restriction, or not obtaining adequate sleep will also result in increased sleepiness and a decline in performance.

Driver fatigue can be produced by active or passive TR fatigue. Active fatigue is the most common form of TR fatigue that drivers experience. Active fatigue is due to mental overload (high demand) driving conditions and passive fatigue is due to under load conditions. Examples of high task demand situations include high density traffic, poor visibility, or the need to complete an auxiliary or secondary task (i.e. searching for an address) in addition to the driving task. Passive fatigue is produced when a driver is mainly monitoring the driving environment over an extended period of time when most or the entire actual driving task is automated. Passive fatigue may occur when the driving task is predictable. Drivers may start to rely on mental schemas of the driving task which results in a reduction in effort exerted on the task. Under load is likely to occur when the roadway is monotonous and there is little traffic.

The measurement of drowsiness is to explore quantitative relationship between drowsiness and driver performance. Drowsiness can be measured by subjective measures, physiological measures and vehicle based measures. Subjective measures of drowsiness involve some form of introspective assessment by the driver. Limitation is that the process of asking for ratings may have stimulated the driver, and therefore reduced the level of drowsiness that is being measured. Vehicle based measures predict drowsiness by monitoring the vehicle speed and steering wheel movement. Sleep deprivation can cause greater variability in driving speed. Sleep-deprived drivers made fewer steering wheel reversals (i.e., movements that crossed the resting position of the wheel) compared to rested drivers.

Physiological measures of drowsiness involve the monitoring of activity in the brain, the heart, and/or the eyes. Two physiological

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measures, in particular, were commonly used: Electro Encephalon Graphic (EEG) activity, and eye blink (or eye closure) duration. In EEG analysis, drowsiness indicators were computed by combining the power in the theta range (4-7 Hz) and alpha range (8-12 Hz). Alpha activity indicates early sign of sleepiness and theta activity is associated with more severe sleepiness. EEG activity in the alpha and theta ranges increased steadily as driving duration increased [3]. Conversely, EEG activity in this range was significantly reduced when drowsy drivers took a nap, or were given caffeine. Although EEG analysis appears to be a reliable tool for validating driver drowsiness, it can be difficult to use in practice, because the EEG signal may be contaminated by artifacts that are caused by body, head, and eye movements. Eye blink duration is effective method to measure drowsiness. One prominent measure for eye blink duration is PERCLOS (percentage of eyelid closure), which is defined as the proportion of time in a specified time period (e.g., 1 to 3 min) that a participant's eyes are closed. According to one criterion, a driver is considered to be drowsy whenever their PERCLOS measure exceeds 80% [4].

An important limitation of using physiological predictors is that driver drowsiness is a very different state to normal drowsiness because drivers are motivated to stay awake. The physiological events that occur before falling asleep at the wheel may therefore be different to those that occur before normal sleep (e.g., at home in bed). Physiological indices of the driver drowsiness state may reflect a mixture of normal drowsiness, and an effortful response to maintain alertness. Eye blinking in the driver is also affected by the outside road lighting, oncoming headlights, and the air temperature and state of the ventilation system in the vehicle.

People in fatigue exhibit certain visual behaviours that are easily observable from changes in facial features such as the eyes, head, and face. Visual behaviours that typically reflect a person’s level of fatigue include eyelid movement, gaze, head movement, and facial expression. To make use of these visual cues, another increasingly popular and non-invasive approach for monitoring fatigue is to assess a driver’s vigilance level through the visual observation of his/her physical conditions using a remote camera and state-of-the-art technologies in computer vision. Techniques that use computer vision are aimed at extracting visual characteristics that typically characterize a driver’s vigilance level from his/her video images.

Despite the success of the existing approaches/systems for extracting characteristics of a driver using computer vision technologies, current efforts in this area, however, focus only on using a single visual cue, such as eyelid movement, line of sight, or head orientation, to characterize driver’s state of alertness. The system that relies on a single visual cue may encounter difficulty when the required visual features cannot be acquired accurately or reliably. For example, drivers with glasses could pose a serious problem to those techniques based on detecting eye characteristics. Glasses can cause glare and may be totally opaque to light, making it impossible for a camera to monitor eye movement. Furthermore, the degree of eye openness may vary from person to person. Another potential problem with the use of a single visual cue is that the obtained visual feature is often ambiguous and, therefore, cannot always be indicative of one’s mental conditions. For example, the irregular head movement or line of sight (such as briefly look back or at the minor) may yield false alarms for such a system.

II. METHODOLOGY

The fundamental block of Drowsiness detection system consists of face detection block, feature extraction block (Eyelid Closure and Yawning Detection) and classification block as shown in Fig.1. Viola jones algorithm is employed for detection of frontal face. Use of integral image representation in viola jones face detector makes the detection faster. Pre-processing stage is optional and operations such as geometric correction, histogram equalization, contrast enhancement, resizing and low pass filtering may be employed for the acquired image prior to feature extraction so as to improve the detection rate. Feature extraction block computes shape and appearance features from the face detected image using HOG feature extractor for the detection of eye blink and yawning state. In the training phase of a classifier the extracted features from train image dataset are used to generate a training model for drowsiness detection system. In test phase, the same feature extracted from the test image is used by the classifier to detect the drowsiness state.

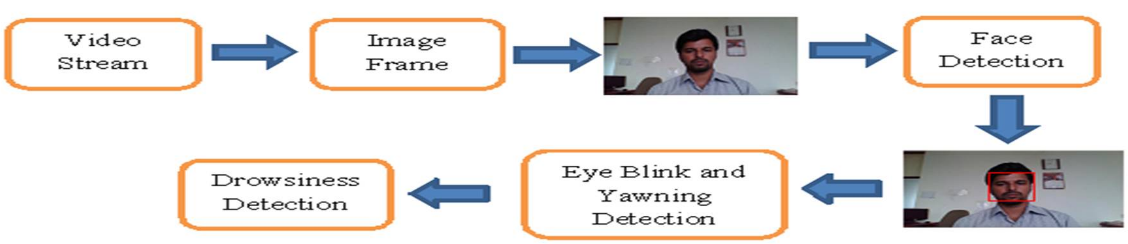

Fig.1: Block diagram of the proposed work.

A. HOG Descriptor

The proposed method uses HOG feature vectors extracted from training images to train the classifier. Characteristics of local shape or gradient structure are better projected by HOG features. It is relatively invariant to local geometric and photometric transformation such that small pose variation doesn't affect performance of FER system. HOG feature vector provides information about shape and appearance of the face which are better characterized by intensity gradients or edge directions. HOG feature extraction algorithm divides static image of a face into small spatial regions known as "Cells". Cells can be rectangular or circular. The image is divided into cells of size N × N pixels and for each cell, gradients are computed using formulations as shown below.

Let f(x,y) represent a single cell in face window.

$$S_h = [-1\ 0\ 1]$$

$$S_v = [-1\ 0\ 1]^T$$

$$g_x = f(x,y) © S_h$$

$$g_v = f(x,y) © S_v$$

$$Orientation = \tan^{-1}(g_v / g_x)$$

S_h — Horizontal gradient operator & S_v — Vertical gradient operator

T — Matrix transform & © — 2D Convolution

g_x — Horizontal gradient of f(x,y) & g_y — Vertical gradient of f(x,y)

Orientation provides gradient feature vector for a single cell. Gradient feature vectors so obtained from each cell of a single image are concatenated to form feature vector for a single image. The feature vectors extracted from images representing different scenarios (eye lid closed, eye lid open, mouth open and mouth closed) are then used for training and testing phases of SVM classifier. Various cell sizes (4,5, 6, 7, 8, 9 and 10) have been tested in the proposed work. Based on the test results, it is rather interesting to note that smaller cell sizes provide large amount of information whereas larger cell sizes provide small amount of information regarding gradient structure. Usage of larger cell sizes cause some useful details to be lost as appearance information of facial image will be squeezed into a single cell histogram. In case of smaller cell size, even though ample amount of information is available classifier demands feature selection in order to extract useful detail from extracted features. The above said issues highlight the importance of cell size for HOG feature extraction. Cell size 7 with 9 Orientation Bins has given good detection results.

B. SVM Classifier

The extracted HOG features are given as input to a group of Support Vector Machines (SVM). SVM is a discriminative classifier defined through a separating hyper plane. SVMs are non-parametric and hence boost the robustness associated with Artificial Neural Networks and other nonparametric classifiers. The purpose of using SVM is to obtain acceptable results in a fast, accurate and easier manner. Linear SVM is employed in the present work. Given some training data D, a set of n points of the form

$$D=\{(x_i, y_i) \mid x_i \in R^p, y_i \in \{-1,1\}\} \quad for\ i=1,2 \ldots\ldots\ldots n$$

Where y_i is either 1 or −1, indicating the class to which point xi belongs. Each point x_i is a p-dimensional real vector. SVM classifier finds the maximum-margin hyper plane that divides the points having y_i=1 from those having y_i= -1. Any hyper plane can be written as set of points x satisfying

$$w \cdot x - b = 0$$

Where '·' denotes the dot product and 'w' the normal vector to a hyper plane. We need to choose 'w' and 'b', which either maximizes the margin or separates parallel hyper planes such that they are as far apart as possible, while still separating the data. These hyper planes can be described by following set of equations

$$w \cdot x - b = 1$$

and

$$w \cdot x - b = -1$$

SVM is a popular machine learning algorithm which maps feature vector to a different plane, usually to a higher dimensional plane, through non-linear mapping, and then finds a linear decision hyper plane so as to classify two classes. SVM classifier is applied in two stages. In the first stage SVM is employed to detect the eye lid status and in the second stage SVM is employed to detect the yawning state. The model of SVM used in the proposed work for eye blink detection is as shown in Fig.2. The model of SVM used in the proposed work for yawning detection is as shown in Fig.3.

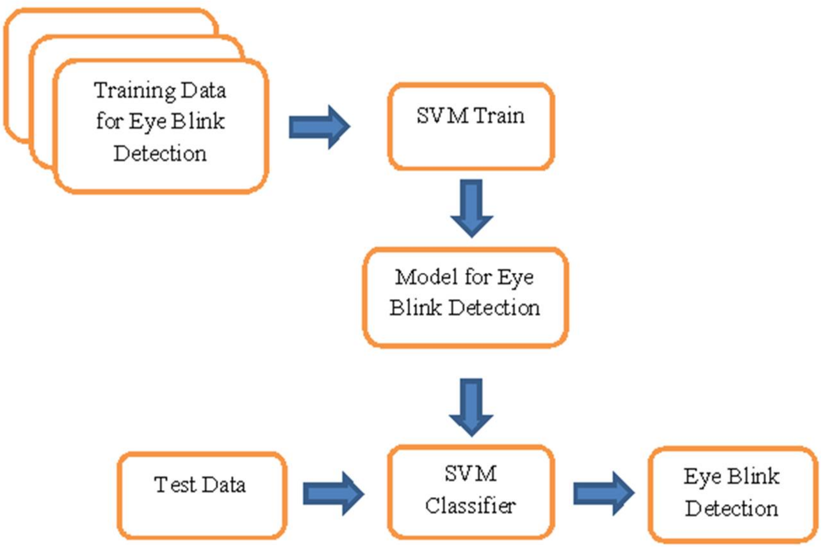

Fig.2: Model of SVM for Eye Blink Detection.

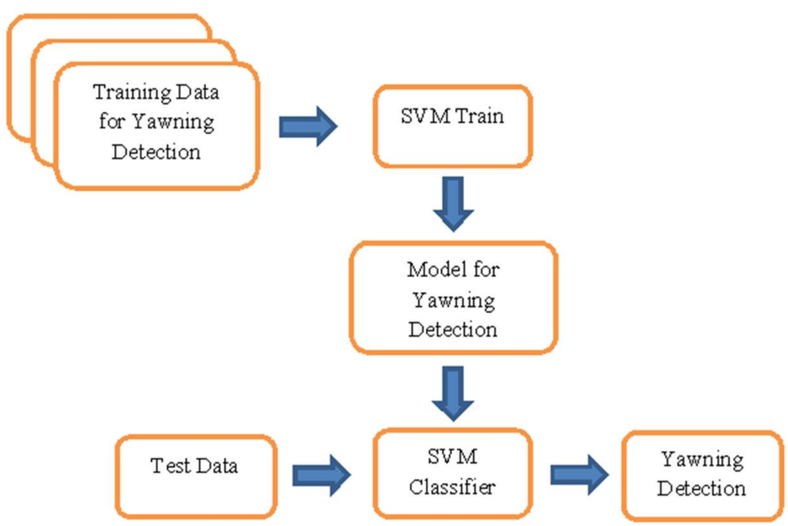

Fig.3: Model of SVM for Yawning Detection.

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C. Flow Chart

The flowchart for the proposed work is as shown in Fig.4. The captured video is transformed into image frames. Face detection algorithm detects face from each frame. HOG feature is extracted from detected face image. The feature extraction technique is same for eye blink detection and yawning detection. The proposed work makes use of two binary SVM classifiers (one for eye blink detection and other for yawning detection). If anyone of the classifier output is true (Closed eye or Open Mouth) for all 20 consecutive frames (one minute) of the test subject then the system outputs as drowsiness detected in the subject under consideration(PERCLOS rule).

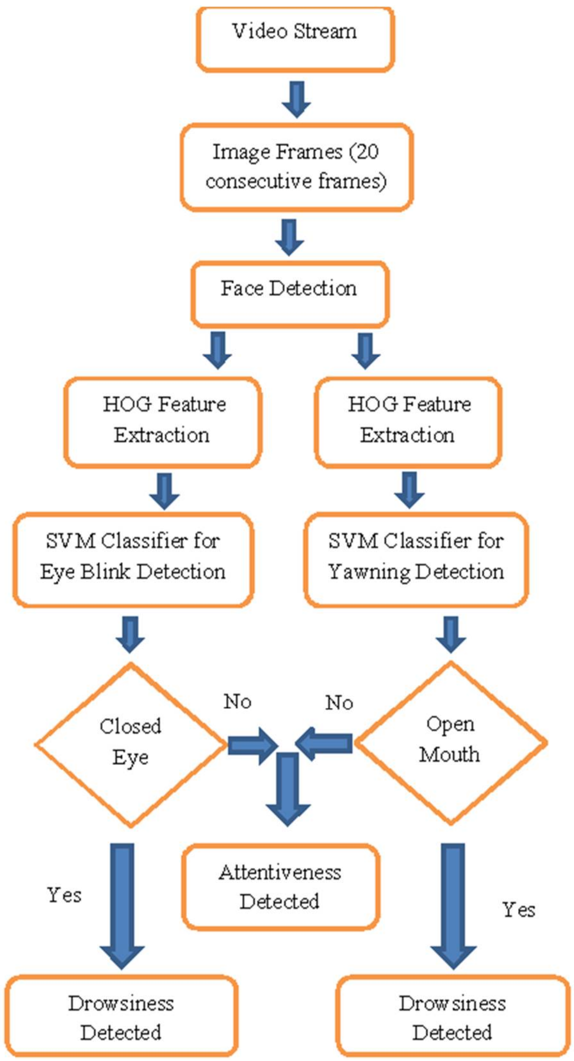

Fig.4: Flowchart for the proposed work.

III.RESULTS AND DISCUSSION

The proposed work is implemented using a data set which consists of image frames obtained from videos of ten different subjects. The data set is partitioned into training dataset and testing data set. Proper attention is taken while preparing database so that the images used for training are not used for testing. The training dataset consists of image frames obtained from videos of six subjects and the test data set consists of image frames obtained from videos of remaining four subjects. From each subject the video is captured in four different scenarios. First scenario indicates subject with closed eye lid, second scenario indicates subject with open eye lid, third scenario indicates subject with open mouth and fourth indicates subject with closed mouth. The shape and appearance feature extracted from image frames which represents the first two scenarios of six subjects are used to train a classifier which is employed for eye blink detection. The shape and appearance features extracted from image frames which represents the third and

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fourth scenarios of six subjects are used to train a classifier which is employed for yawning detection. During testing phase the same shape and appearance feature is extracted from the test image frame to identify the drowsiness state. If the eyelid is closed or if the mouth is open in all the consecutive 20 frames (one minute) the system outputs as the subject under testing is feeling drowsy. The results of the proposed work for different scenarios are as shown in Fig. 5 and Fig. 6.

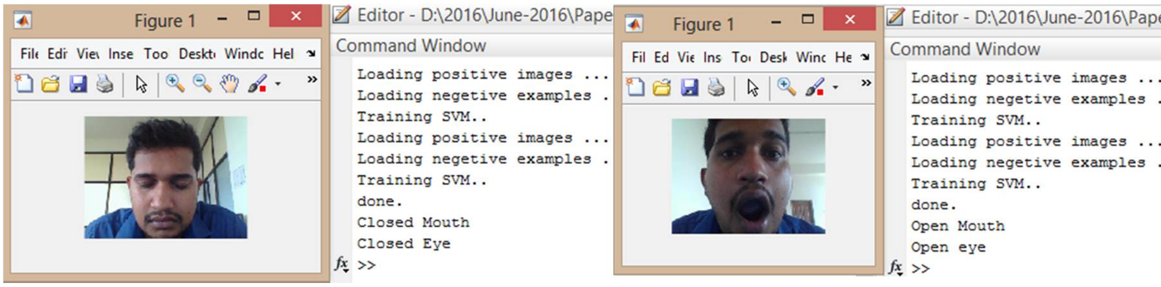

Fig.5: Results of the proposed work.

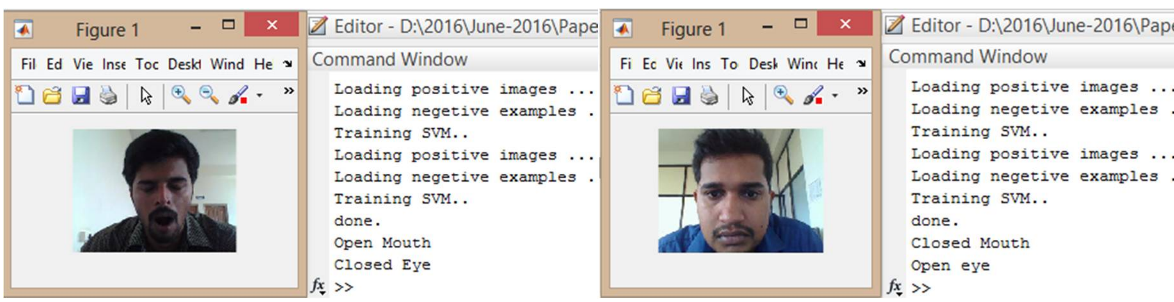

Fig.6: Results of the proposed work

The detection rate was found to be good for cell size 7 with 9 orientation bins from the experiments carried out. Proposed model achieved detection rate of 93%. The use of HOG for feature extraction technique makes the model more robust to age, gender and small pose variations (head nodding and shaking).

IV. CONCLUSION

Challenges involved in drowsiness detection and existing methods for the same were discussed. In the proposed work advanced image processing technique is employed for drowsiness detection which can reduce traffic accidents when implemented in real time. Drowsiness state is identified by monitoring the eye blink status and yawning condition. The model for drowsiness detection system uses HOG for feature extraction and SVM for classification. The detection rate of the proposed work was found to be 93%. Result shows that the proposed model is the best physiological measure for drowsiness when compared to subjective measures, EEG based physiological measures and vehicle based measures. The use of HOG for feature extraction technique makes the model more robust to age, gender and small pose variations (head nodding and shaking).

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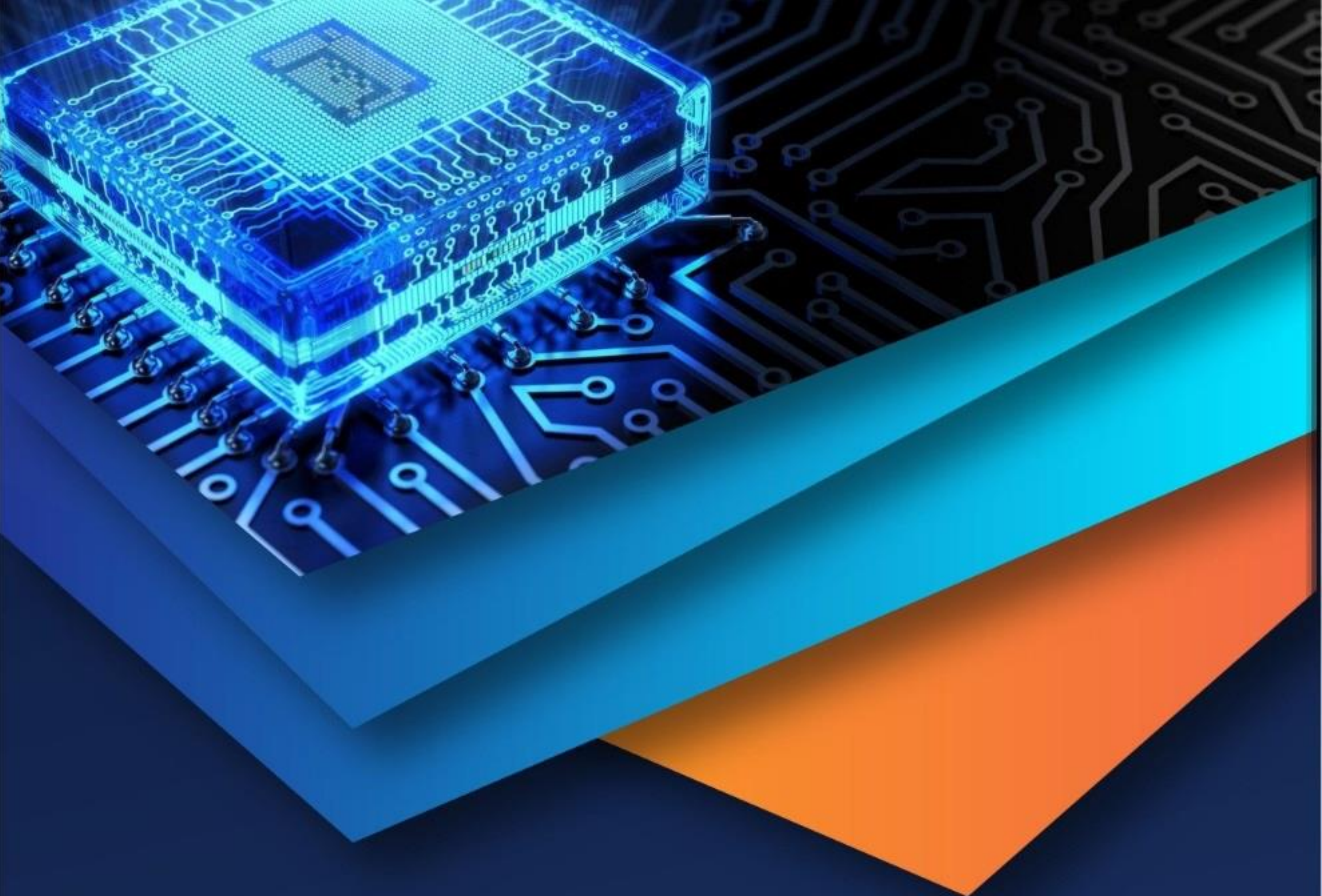

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