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Automatic Moving Vehicle Detection and Number Plate Recognition System

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Abstract: Automatic recognition of car license plate number became a very important in our daily life because of the unlimited increase of cars and transportation systems which make it impossible to be fully managed by humans. So here a method of vehicle tracking and motion detection based on background subtraction and the number plate detection is developing. The main objective of this work is to show a system that solves the practical problem of car identification for real scenes. All steps of the process, from video acquisition to optical character recognition are considered to achieve an automatic identification of plates. This system has wide range of applications such as traffic monitoring, tracking stolen cars, managing parking toll, red-light violation enforcement, border and customs checkpoints etc. Yet it's a very challenging problem, due to the diversity of plate formats, different scales, rotations and non-uniform illumination conditions during image acquisition. This paper mainly introduces an Automatic Number Plate Recognition System (ANPR) using Morphological operations, Histogram manipulation and Edge detection Techniques for plate localization and characters segmentation. Artificial Neural Networks are used for character classification and recognition. Artificial Neural Networks are used for character classification and recognition.
Keywords: Morphological operations, Sobel edge detection, Adaptive histogram equalization, Character segmentation, Connected component analysis, Artificial Neural Network, Optical character recognition, feed forward neural network

I. INTRODUCTION

The increased use of vehicle in recent years led to pay more attention to new technologies in transportation system. The Intelligent Transport systems have a wide impact in people's life. Conventional techniques for traffic measurements, such as inductive loops, sensors or EM microwave detectors, suffer from serious shortcomings, expensive to install, bulky and unable to detect slow or temporary stop vehicles. Systems based on videos allow measurement of vehicle's speed, counting the number of vehicles, classification of vehicles, and the identification of traffic incidents. Automatic number plate recognition and the moving vehicle tracking becomes more useful in high security places. It has so many applications like tracking stolen cars, managing parking toll, border and customs checkpoints, automatic toll tax collection, access control in security sensitive areas, securities for communities and important buildings, detection of military target areas, traffic, traffic control management etc. Localization of number plate from vehicle images is a challenging task due to variations in size, shape, texture and spatial orientations.

Here morphological operations and edge detection algorithms are using for number plate localization. Background subtraction method using low rank and structured sparse decomposition is done for tracking the moving vehicle in the security places, traffic, parking areas etc. Here the number of vehicles passed in that location is also predicting by detecting the moving object with the help of background subtraction. It focuses on the image processing algorithm in ANPR system which is simulated in MATLAB software. After the image acquisition is done the image is processed with the pre-processing stage before giving to the number plate localization. Histogram manipulation and edge detection techniques are using for number plate localization. Artificial neural networks are used to recognize the number in the final stage.

II. OBJECTIVES

The automatic number plate recognition methods are becoming more important in the coming years. It can be used for traffic rule violation, managing toll collection, identifying stollen cars etc. The background subtraction using Low rank and Structured Sparse Decomposition is used for detecting the moving vehicle. In traffic the congestion problem can be found and moving vehicle can be identified easily even in far away by using the background subtraction. The motion of vehicle even behind the leaves of trees and any other obstructions cannot be identified easily. It will be more useful in high security places like militaries. Along with this method Automatic number plate recognition also developed by using histogram manipulation and artificial neural networks. It provides more efficient recognition and gives clear recognition even for low quality images. The number plates can be detected easily after the background subtraction of vehicle as prediction of vehicle is done. Thus, we can identify the vehicle's information easily by analysing the data that previously collected.

III. LITERATURE REVIEW

Many researchers have contributed in development of ANPR. The related work of some of the researchers is presented here.

Automatic Number Plate Recognition System: Amr Badr et al. [5] developed a number plate recognition system in the Egyptian number plates. In this, an alternative solution to the image segmentation and character recognition problems within the License Plate Recognition framework is done. They used a feed forward artificial neural network trained with back propagation with sigmoid activation function and the ANN is trained on the chain code feature. They are not using the vehicle tracking and background subtraction methods. Efficient Car License Plate Detection and Recognition by Using Vertical Edge Based Method: M. Veerraju et al. [6] proposed a VEDA for the number plate recognition. For that accurate identification of number plate region, structured component algorithm is used. Identified group of characters will be compared with template of database numbers with grant of access to get accurate number plate region. In this the rate of correctly detected LPs is high. Also, the computation time of the CLPD method is low, which meets the real-time requirements. The characters alone cannot be recognized in VEDA. Automatic Vehicle Detection, Tracking and Recognition of License Plate in Real Time Videos: Lucky Kodwani [7] proposed a tracking and recognition system using Sobel edge detection and a Block variance algorithm. They use template matching for the character recognition. The block variance algorithm has been tested on 90 images and giving 87.4% accuracy measure. The system works well either in real time mode or in already stored video. In this all font types of characters are cannot be identified accurately.

Vehicle Plate Number Detection and Recognition Using Improved Algorithm: Cosmo H. Munuo et al. [8] proposed a method by using algorithms for different stages. HSV color space image, morphological and statistical analysis operations were integrated and employed to a vehicle image to compute plate number area. The connected components were computed to provide the actual plate area position or coordinates of the region of interest. Finally, statistical analyses were applied to find the connected components to be used to locate number plate accurately. Character extraction algorithm consists of global and local searching. The masked image was computed using function (dim (1), dim (2)), where dim (1) computed rows and dim (2) computed columns. The HSV color space image, morphological and statistical analysis operations were integrated to compute plate number area which was region of interest (ROI). The HSV color space image, morphological and statistical analysis operations were integrated to compute plate number area which was region of interest (ROI). The recognition was done by comparing each extracted character to all the templates in the database and the one with maximum resemblance was picked. Automatic Parking Management System and Parking Fee Collection Based on Number Plate Recognition: M. M. Rashid et al. [9] proposed a different method of number plate recognition. A full display system, structural similarity index and a direction system are used in the character recognition. An electronic payment system is also used here. The developed algorithms accurately localize and recognize in different location of the license plate. Electronic billing system performance is also acceptable.

IV. PROPOSED METHOD

In the proposed method a background subtraction algorithm for moving vehicle detection and number plate recognition system using histogram manipulation and artificial neural network is done. It focusing on the image processing algorithm in ANPR system which is simulated in MATLAB software. The ANPR system consists of following steps:

1) Image acquisition
2) Preprocessing
3) Number plate extraction
4) Character segmentation
5) Character recognition

The initial step is the image acquisition. The image is captured using the static camera. Then this is given to pre processing stage. It modifies the image for the better recognition accuracy. Then the number plate is extracted in next step. Then it is given to the character segmentation. This stage separates each character and this character is given to the character recognition.

A. Low-Rank and Structured Sparsity decomposition (LSD) for foreground detection

1) *Structured Sparsity-Inducing Norms for Modeling Sparse Outliers:* Background subtraction is a widely used approach for detecting moving objects in videos from static cameras. Here we proposing a method with a low rank matrix and a sparse matrix which separates foreground and background. A matrix composed of the observed video frames can be decomposed into a low-rank matrix representing the background and a sparse matrix consisting of the foreground objects treated as the sparse foreground. In the decomposition, the outlier support and the low-rank matrix are estimated simultaneously. The static setting of the regularizing parameter is replaced by the adaptive settings for image regions with distinct properties for each frame.

Hence, the proposed method is able to tolerate sudden background variations like the changing weather conditions or turn on/off lights, without losing sensitivity. The observed matrix D ϵ Rm∗n and the frame at time t , D= {I1……In}, and n is the total number of frames. To encode the prior knowledge, we consider the structured sparsity-inducing norm that involves overlapping groups of variables.

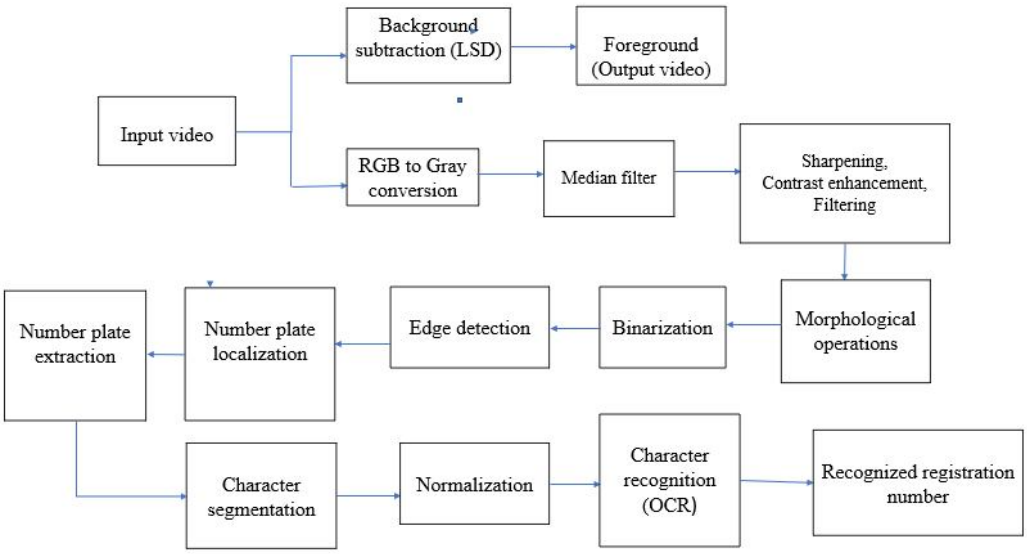

Fig. 1 Block diagram of the proposed method

The structured sparsity norm can reflect the spatial distribution of nonzero variables and thus promote the structural distribution of sparse outliers during the minimization. Different distributions of a sparse foreground in an 8*8 (m = 64) sized image (see Fig.2) shows that white pixels correspond to outliers with high values and black pixels correspond to small values. Since the `1-norm sums up the absolute values of all pixels, it will have similar values in two cases (Fig. 2 (a, b)).

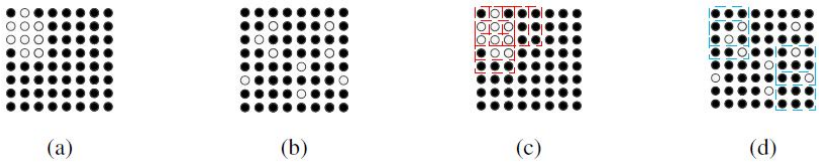

Fig. 2 (a)-(b) Two distributions of sparse entries in a 8 * 8 frame. (c)-(d) Several 3*3 overlapping groups on two cases.

The structured sparsity norm only sums up the largest one in each pre-designed group (36 overlapping groups in 8*8 frame), and hence it will have distinct different values: the value in the first case (Fig. 2 (c)) is much smaller than that in the latter case (Fig. 2(d)) because more groups containing large value pixels appear in the latter case (Fig. 2 (d)). To formalize structure prior on the outliers and also promote structured sparsity of sparse outliers, we introduce the structured sparsity norm and then propose Low-rank and Structured sparse Decomposition (LSD) method. The optimization problem can be solved by Augmented Lagrange Multiplier (ALM).

2) *Foreground Group Candidates via LSD:* Firstly, we found that a structured sparsity based RPCA scheme can better estimate background, but it is also sensitive to some dynamic background motions. Hence, the obtained candidate groups denote both foreground objects and a few background motions. Note that pixels identified as outliers in the low resolution image correspond to a 4 ∗ 4 regions in the full resolution image.
3) *Motion Saliency Check:* Secondly, the likelihood of a group containing foreground should be checked out and those with little motions should be suppressed. Since background motion is usually smaller and more regular than foreground object motion, the foreground object will form a distinct trajectory from the background in a temporal slice on the X-T and Y-T planes. The analysis of temporal slices will detect such distinct trajectories of foreground objects and generate a motion saliency map. In the motion saliency map, larger values typically correspond to the more motion salient pixels.

Fig. 3 Background subtraction using LSD

Fig. 4 Background subtraction of input vehicle

B. Image Acquisition

The initial step is the Acquisition. Image capture is done in two ways: Using an Infrared camera and using a High Resolution (HR) Digital Camera. Here HR digital camera is using and collected images in JPG format. The captured image taken from 4-5 meters away is processed through the License Plate extractor with giving its output to segmentation part. The images are in RGB format so it can be further process for the Number Plate Extraction. The image optained in this stage is shown in fig. 5

Fig. 5 input vehicle image optained with HR digital camera

C. Image Pre processing

To improve the contrast of the input image, to reduce the noise in the image, hence to enhance the processing speed pre-processing is necessary. In this, RGB image is converted into gray level image and then into binary image. The contrast enhancement is done by histogram equalization, contrast stretching etc. Various filters are used to remove noise from the input image. The following transformations are applied on the colour image:

1) *Conversion of RGB image into a Gray-scale image:* The RGB colour image which is got in the previous stage is converting into Grayscale image, because all the further processing is done in Grayscale format. Grayscale is chosen because of its simplicity and for its two-dimensional matrix nature, also it contains enough information needed for the actual recognition. The basic purpose of applying color conversion is to reduce the number of colors. The conversion is performed by using the MATLAB function *rgb2gray*. From 24-bit color value of each pixel (i,j) R, G and B components are separated and 8-bit gray value is calculated using the formula:

$$grey(i,,j) = 0.59 * R(i, j) + 0.30 * G(i, j) + 0.11 * B(i, j)$$

The luminance of a pixel value of a grayscale image ranges from 0 to 255. Where, *(i, j)* indicates the position of a pixel in the image, and gray (i, j) belongs (0, 255). The interested region is cropped and converted to grayscale format since it would reduce processing time as well as the complexity of the algorithm. It is then enhanced in order to make the edges more distinct. When the image is converted from RGB to grey image, certain important parameters like difference in colour, lighter edges of object, etc may be lost.

2) *Conversion of Gray scale image into a Binary image:* In this stage a binary image from the gray scale image is producing by comparing pixel intensities with a threshold. The threshold for binarization can be two types static or dynamic. In static general threshold is taken 150 (in gray scale of 0-255). This value reasonably quantizes those pixels, which represents the license plate and any other portions, which has a pixel-value more than the selected threshold. The remaining portions, which have a pixel-value less than the threshold value, are darkened. In dynamic threshold, the threshold taken will be the average of low and median gray scale values. The conversion is done by using the MATLAB function *im2bw*.
3) *Median Filtering:* Median filter is a non-linear filter, which replaces the gray value of a pixel by the median of the gray values of its neighbors. It is used to remove noise from an image or signal. The center pixel of a $M \times M$ neighborhood is replaced by the median value of the corresponding window. A 3 × 3 mask is using to get eight neighbors of a pixel and their corresponding gray values. The gray value of center pixel of mask is replaced by the median of gray values of pixels within the mask. This operation removes salt-and-peeper noise from image. The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. It replaces pixels with the *median* of those values. The median of n observations xi i = 1... n is denoted by med (xi) and it is given by:

$$\text{med}\,(x_i) = \begin{cases} x_{v+1} & n = 2v+1 \\ \frac{1}{2}(x_v + x_{v+1}) & n = 2v \end{cases}$$

where x(i) denotes the i-th order statistic. A one-dimensional median filter of size n =2v+ 1 is defined by the following input-output relation:

$$yi = med(xi-v, \ldots, xi, \ldots xi+v)$$

Its input is the sequence xi, i ∈ Z and its output is the sequence yi, I ∈Z. Definition is also called moving median or running median.

4) *Contrast Enhancement using Histogram:* Contrast of each image is enhanced through histogram equalization technique. Total 256 numbers of grey levels (from 0 to 255) are used for stretching the contrast. Let the total number of pixels in the image be N and the number of pixels having grey level k be nk. Then the probability of occurrence of grey level k is $Pk=nkN$. The stretched grey level Sk is calculated using the cumulative frequency of occurrence of the gray level k in original image using the formula:

$$S_k = \sum_{j=0}^{k} \frac{n_j}{N} \times 255$$

255 is the maximum grey level in the enhanced image

A histogram for the edges processed in the horizontal direction is plotted and it is then passed through an averaging filter to smoothen the varying transitions. The smoothened histogram is passed through an averaging process that highlights the regions that could contain the license plate.

The search is further narrowed down by incorporating the largest column in the histogram. Histogram equalization cannot be applied separately to the Red, Green and Blue components of the image as it changes image's color balance. Adaptive Histogram Equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. In Contrastive Limited Adaptive Equalization Contrast Limited AHE (CLAHE) differs from adaptive histogram equalization in its contrast limiting. The histogram for a very dark image will have most of its data points on the left side and center of the graph. Conversely, the histogram for a very bright image with few dark areas and shadows will have most of its data points on the right side and center of the graph.

5) *Number Plate Localization :* This stage aims on license plate extraction and begins with color to gray conversion. For accurate location of the license plate the vehicle must be perfectly visible. Sometimes the image may be too dark, contain blur, making the extraction of license plate difficult. The variance provides information about the visual properties of the image. Based on this, condition for contrast enhancement is employed. Firstly, variance of the image is computed. With an aim to reduce computational complexity the proposed implementation begins with the thresholding of variance as a selection criterion for frames aspiring contrast enhancement. If the value is greater than the threshold then the corresponding image possesses good contrast. While if the variance is below threshold, then the image has low contrast and contrast enhancement is applied to it. In this work, first step towards contrast enhancement is to apply unsharp masking on original image and then applying the sigmoid function for contrast enhancement. Sigmoid function also known as logistic function is a continuous nonlinear activation function. It is a range mapping approach with soft thresholding. Using f(x) for input, and with α as a gain term, the sigmoid function is given by:

$$f(x) = \frac{1}{1 + e^{-\alpha x}}$$

The segments having area within a predetermined range are only considered as valid segments. All the remaining segments are considered as noise.

6) *Aspect Ratio of the Segment:* Any single line license plate has a standard aspect ratio (AR1) and double line license plate has aspect ratio (AR2). It is defined as the ratio of the height to the width of the region's rectangle. In vehicles consisting of two row license plate aspect ratio varies nearer to 0.6. If the aspect ratio of any segment does not lie within a tolerable limit (±η) of the aspect ratio, then it is considered as a noise segment. If any segment satisfies the requisite attribute for the area and the aspect ratio, then the vertical edge gradients of the said segment is analyzed. Using the Sobel's edge operator, mean (μ) vertical edge gradient and the standard deviation (σ) for the same are estimated within each such segment. Since the alphanumeric characters, present within the license plates have significant vertical edge components, the vertical edge signature within any segment is considered as an important attribute for the designed segment analysis engine. The segments having $\mu > \mu th$ and $\sigma > \sigma th$ are finally considered as the potential license plate regions.
7) *Mathematical Morphology:* The Mathematical morphology uses the elements with a certain shape to measure and extract the corresponding shape in the image for analysis and recognition, and noise reduction. Firstly, we use the method of statistical color pixel to determine the range of gray scale of license plate that corresponds to RGB. Next the number of pixels in the rows and columns are counted. Then, we get orientation matrix of the license plate region, and remove the unnecessary part to obtain the license plate images that are located already. A small shape or template called a structuring element, a matrix that identifies the pixel in the image being processed and defines the neighborhood used in the processing of each pixel is used to probe an image. It is positioned at all possible locations in the input image and compared with the corresponding neighborhood of pixels. Commonly these structuring elements have odd dimensions and the origin defined as the centre of the matrix. The main technology is to calculate the projection area of the edge image to find the peak point and determine the position of the license plate. Then calculate aspect ratio of the connected domain and weed out the connected domain that doesn't fit in the threshold value range for obtaining the region of license plate. The basic morphological operators are erosion, dilation, opening and closing. An *origin* of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element.
8) *Morphological Dilation and Erosion:* Dilation represented by the symbol $\oplus$. The assigned structuring element is used for probing and expanding the shapes contained in the input image. It acts like local maximum filter. Dilation has the opposite effect to erosion. It adds a layer of pixels to both the inner and outer boundaries of regions. That is, the value of the output pixel is the maximum value of all pixels in the neighborhood. In a binary image, a pixel is set to 1 if any of the neighboring pixels have the value 1. Morphological dilation makes objects more visible. The dilation of an image f by a structuring element s (denoted $f \oplus s$) produces a new binary image $g = f \oplus s$ with ones in all locations (x, y) of a structuring element's origin at which that structuring element s hits the input image f, i.e. $g(x, y) = 1$ if s hits f and 0 otherwise, repeating for all pixel coordinates (x, y). Erosion is represented by the symbol $\ominus$. The assigned structuring element is used for probing and reducing the shapes contained in the input image. It acts like local minimum filter. Also, the structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The value of the output pixel is the minimum value of all pixels in the neighborhood. In a binary image, a pixel is set to 0 if any of the neighboring pixels have the value 0.

Morphological erosion removes islands and small objects so that only substantive objects. The erosion of a binary image *f* by a structuring element *s* (denoted $f \ominus s$) creates a new binary image $g = f \ominus s$ with ones in all locations (x, y) of a structuring element's origin at which that structuring element s fits the input image *f*, i.e. $g(x, y) = 1$ is s fits f and 0 otherwise, repeating for all pixel coordinates (x, y).

9) *Opening and Closing:* Opening is represented as ($A \circ B = (A \ominus B) \oplus B$). It removes any narrow connections and lines between two regions. The opening operation erodes an image and then dilates the eroded image, using the same structuring element for both operations. Morphological opening is useful for removing small objects from an image while preserving the shape and size of larger objects in the image. The opening of an image *f* by a structuring element *s* denoted by $f \circ s$. Closing is represented as ($A \bullet B = (A \oplus B) \ominus B$). The closing operation dilates an image and then erodes the dilated image, using the same structuring element for both operations. Morphological closing is useful for filling small holes from an image while preserving the shape and size of the objects in the image. The closing morphological operation performed on an image f by a structuring element s denoted by $f \bullet s$.

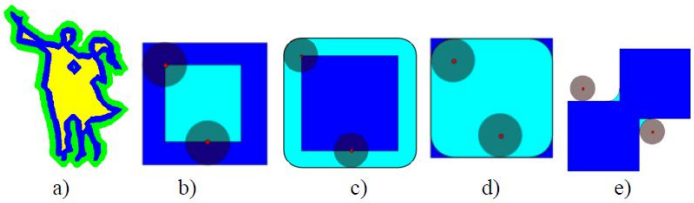

Fig. 6 a) diamond shaped structuring element b) erosion c) dilation d) opening e) closing

In Fig. 6 a) A shape (in blue) and its morphological dilation (in green) and erosion (in yellow by a diamond shaped structuring element. In b) erosion of dark blue square by a disc resulting in light blue square. In c) The dilation of dark blue square by a disc resulting in light blue square with rounded corners. In d) The opening of dark blue square by a disk resulting in the light blue square with rounded corners. In e) The closing of the dark blue shape (union of two squares) by a disk resulting in the union of the dark blue shape and the light blue area.

10) *Filtration of non-License Plate Region:* Various features such as the size, width, height, orientation of the characters, edge intensity, etc can be helpful in filtering of non-license plate regions. In this algorithm, rectangularity, aspect ratio analysis and plate companionable filter are defined in order to decide if a component is a license plate or not. These features are not scale-invariant, luminance-invariant, rotation invariant, but they are insensitive to changes like contrast blurriness and noise. Plate Companionable Filter is used to avoid misrecognize as candidates even after aspect ratio analysis. The variations between plate background and characters are used to make the distinction. If the count value at the prescribed scanning positions which are H/3, H/2 and (HH/3) correspondingly, where H is the height of the component, is more than desired threshold then it is considered as a license plate else it is discarded from the region of interest.

D. Edge Detection

There are so many types of edge detection methods. Sobel method, Prewitt method and Roberts method finds edges of an image using the approximation to the derivative. It produces edges at those points where the gradient of an image is maximum. The Laplacian of Gaussian method finds edges by looking for zero crossings after filtering an image with a Laplacian of Gaussian filter. The gradient is calculated using the derivative of a Gaussian filter. This technique employs two thresholds, to identify strong and weak edges, and comprises the weak edges in the output only if they are connected to strong edges. Out of all these, Sobel edge detection gives the better results. So Sobel edge detection is taken. The conversion is performed by using the MATLAB function *edge.*

1) *Sobel edge detection:* Sobel operator preserves majority of edge information in the plate area while it removes lots of horizontal edges around the LP results in localization process easier and the computational time of Sobel operator is low. The computation of the partial derivation in gradient may be approximated in digital images by using Sobel operator. A convolution mask is used is usually much smaller than the actual image. As a result, the mask is slide over an area of the input image, changes that pixel's value and shifts one pixel to the right and continues to the right until it reaches the end of a row. It then starts at the beginning of the next row. The center of the mask is placed over the pixel you are manipulating in the image. And to multiply, the values are used to move the file pointer. After the edges are detected, a binary edge map is obtained by adaptive binarization.

The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges. Typically, it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. Given the binarized image we perform vertical edge detection with *mask A* and horizontal edge detection with *mask B*. Since we are not interested in the direction of the edge, we take the absolute value of the output of the mask to obtain edges present in all four directions. Wherever an edge is present we mark the pixel as a 1, otherwise, we mark it 0. If the binarization threshold is appropriate, performing edge detection on the black and white image should result in a great deal of edges in the area of the license plate due to the characters. The edge detector will detect much thinner edges in addition to the edges of the characters of the license plate. If we define A as the source image, and G*x* and G*y* are two images which at each point contain the vertical and horizontal derivative approximations respectively, the computations are as follows:

-1	0	+1
-2	0	+2
-1	0	+1

G_x

+1	+2	+1
0	0	0
-1	-2	-1

G_y

Fig. 8 Sobel convolution kernels

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation. The *x*-coordinate increasing in the "right"-direction, and the *y*-coordinate increasing in the "down"-direction. At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using:

$$|G|=\sqrt{G_x{}^2+G_y{}^2}$$

Typically, an approximate magnitude is computed using:

$$|G| = |Gx|+|Gy|$$

CAR 1 CAR 2

Fig. 9 Sobel edge detected Images (a) CAR-1 (b) CAR-2

E. Character Extraction

1) *Histogram approach:* In license plate extraction license plates are extracted using various available techniques. Here first license plate image is cropped in lines, and then characters are segmented and recognized. Histogram equalization can be used to improve the results of edge detector. Vertical lines in the license plate are typically more than a factor four shorter than the horizontal lines and thus more susceptible to noise. taking row wise histogram and using threshold we can detect the boundaries. In Y-histogram a uniformly distributed pattern of low-valued breaks between characters is detected, whereas in X-histogram the top and bottom borders of the character set. As we are finding the area which contains license plate, rotation of the plate will not affect the algorithm. The spots remaining after the previous stage are arranged in the form of a string and are treated as possible license plate characters.

F. Number Plate Segmentation

The segmentation is one of the most important processes in the automatic number plate recognition, because all further steps rely on it. If the segmentation fails, a character can be improperly divided into two pieces, or two characters can be improperly merged together. We can use a horizontal projection of a number plate for the segmentation using the neural networks. If we assume only one-row plates, the segmentation is a process of finding horizontal boundaries between characters. The second phase of the segmentation is an enhancement of segments. The segment of a plate contains character and also undesirable elements such as dots and stretches as well as redundant space on the sides of character. To simplify the process of identifying the characters, it is desirable to separate the extracted plate into several images. Then each character will be classified as a connected component.

1) *Using Projection Profiles:* Other methods for number plate segmentation are based on the extraction and analysis of the projection profiles of the number plate image. These represent the running sum of the values of the pixels of an image in horizontal or vertical. Since all the number plates share the common structure of several black alphanumeric characters in a row on a white or yellow background, their projection profile has a characteristic shape that can be used to detect the position of the characters. In this method they are totally independent of the position of the characters and able to deal with a certain degree of number plate rotation. They are greatly affected by noise and needing a prior knowledge of the exact number of characters appearing in the number plate. An example of these methods would be: Vertical projection of the binary extracted number plate.
2) *Using prior Knowledge of Characters:* It is based on the idea that if the positions and number of characters appearing in the number plate are previously known. It is not difficult to extract these characters by using a template. They constitute very simple methods. They are limited by the prior knowledge of the number plate format and any change in it can affect the result of the number plate segmentation. Some examples of these methods are: number plate scanning or number plate resizing into a known template size.
3) *Segmentation of Plate using a Horizontal Projection:* The adaptive thresholding filter is applying to enhance an area of the plate before segmentation. It is used to separate dark foreground from light background with non-uniform illumination. After the thresholding, we compute a horizontal projection of the plate $f(x, y)$. We use this projection to determine horizontal boundaries between segmented characters. These boundaries correspond to peaks in the graph of the horizontal projection (figure 10.b). The goal of the segmentation algorithm is to find peaks, which correspond to the spaces between characters. At first there is a need to define several important values in a graph of the horizontal projection $Px(x)$. Vm is the maximum value contained in the horizontal projection $Px(x)$. Va is the average value horizontal projection. Vb is the value used as the base for evaluation of peak height.

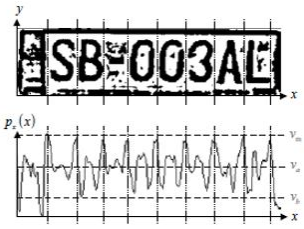

Fig. 10 a) number plate after application of the adaptive thresholding, b) horizontal projection of plate with detected peaks

4) *Extraction of Characters from Horizontal Segments:* The segment of plate contains the character also redundant space and other undesirable elements. Since the segment has been processed by an adaptive thresholding filter, it contains only black and white pixels. The neighboring pixels are grouped together into larger pieces, and one of them is a character. Our goal is to divide the segment into the several pieces, and keep only one piece representing the regular character. This concept is illustrated in fig 11.

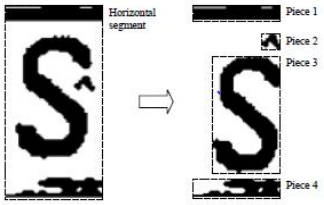

Fig. 11 Horizontal segment of the number plate contains several groups of neighboring pixels.

Find the number and location of the horizontal group using binarisation and lateral histogram analysis. Because the edges of the characters can be blurred, noise of various types can partially cover characters or make connections between different characters and characters and borders. Classical methods based on morphological analysis of the characters and edge detection is using. It is assumed that the characters which form the registration number are grouped together in one or two horizontal groups. If there are two horizontal groups, their heights do not overlap. There is no restriction for the number of characters.

Adaptive thresholding techniques have shown to be more flexible but they are not reliable. In binarisation firstly we calculate the histogram and smooth it with a repeated gaussian filter in order to eliminate small local peaks and troughs. Then look for high, non-local peaks. These are peaks which differ from the nearest local minimum by a certain minimum amount which is taken to be a percentage of the vertical size of the interest area. If the highest two peaks correspond to intensity values which differ by a minimum amount and the median falls in-between the two peaks, then the threshold is set midway between these peaks. If the difference between the heights of these two highest peaks is larger than a certain relative limit, correct the threshold with a bias adjustment factor. If the highest two peaks correspond to intensity values which are closer than the minimum amount, or if the median does not fall in-between the two peaks, ignore the second highest peak and try to find another one which satisfies the condition. If such a peak is found, proceed as before. If such a peak is not found (the histogram is unimodal), scan the histogram from its peak down until the width becomes sufficient. Take the threshold at half the width and check whether this value is close to the median. If yes, accept this value else reject and rely on the adaptive binarization.

5) *Connected Component Analysis (CCA):*This approach is used to uniquely label subsets of connected components based on a given heuristic. It scans binary image and labels pixel as per connectivity conditions of current pixel such as North-East, North, North-West and West of the current. It can be used in plate segmentation as well as character segmentation. Connected Component Labelling (CCL) is used for LPD. CCL scans the image and labels the pixels according to the pixel connectivity. It must be determined if they are neighbours and if their gray levels satisfy a specific criterion of similarity. There are two types of connectivity: 4 and 8 connectivity. A feature extraction algorithm [8] is used to count the similar labels to distinguish it as a region. The region with maximum area is considered as a possible license plate region and this region is forwarded to the segmentation process.
6) *Normalization of Brightness and Contrast*: By the histogram normalization, the intensities of character segments are redistributed on the histogram to obtain the normalized statistics. Techniques of the global and adaptive thresholding are used to obtain monochrome representations of processed character segments. Consider a grey scale image defined by a discrete function f(x,y). Let I be a total number of gray levels in the image. We use histogram to determine the number of occurrences of each gray level i , $i \in 0 \ldots I-1$. The global thresholding is an operation when a ccontinuos gray scale of an image is reduced into black and white colors according to the global threshold value. Let (0,1) be a gray scale of such image. If a value of a certain pixel is above the threshold t, the new value of the pixel will be zero. Otherwise, the new value will be one for pixels with values above the threshold t. In Adaptive thresholding the number plate can be sometimes partially shadowed or nonuniformly illuminated. This is most frequent reason why the global thresholding fails. It computes threshold value for each pixel separately using its local neighborhood.
7) *Feature Extraction:* Information contained in a bitmap representation of an image is not suitable for processing by computers. The description of the character should be invariant towards the 36 used font type, or deformations caused by a skew.

$$X = (x0, \ldots, xn-1))$$

Generally, the description of an image region is based on its *internal* and *external* representation. The internal representation of an image is based on its regional properties, such as color or texture. The external representation is chosen when the primary focus is on shape characteristics. The description of normalized characters is based on its external characteristics because we deal only with properties such as character shape. Then, the vector of descriptors includes characteristics such as number of lines, bays, lakes, the amount of horizontal, vertical and diagonal or diagonal edges etc.

G. Characters Recognition

The aim of character recognition is to employ conversion of image text to characters. The extracted characters are recognized and the output is the license plate number. In this chapter we introducing the pattern recognition technique artificial neural networks. The license plate contains any character from A to Z and number from 0 to 9. Due to the camera zoom factor, the extracted characters do not have the same size and the same thickness. Resizing the characters helps overcome this problem. The character recognition techniques include Template Matching, Artificial Neural Networks (ANNs), Support Vector Machines (SVM) and Optical Character Recognition (OCR).

1) *Optical Character Recognition (OCR):* Optical Character Recognition (OCR) is a type of image analysis method. A digital image that contains either machine readable or handwritten characters is input into an OCR software engine and translating it into an editable machine-readable digital text format. The method consists of three steps: character categorization, topological sorting and self-organizing (SO) recognition. Character categorization is used to classify character as alphabet or number. The main challenge in character recognition is to handle unknown text layout, different font sizes, different illumination conditions, reflections, shadowing and aliasing.
2) *Artificial Neural Network (ANN):* Artificial Neural Network (ANN) is a mathematical term that contains interconnected artificial neurons. The feed forward back propagation artificial neural network is created with the set of inputs, outputs and hidden layers. It contains input layer for decision making, hidden layer to compute more complicated associations and output layer for decision results. The network is trained with the training data set which includes feature value as input and desired output in the system. After training, it is tested for the test data set and accuracy is calculated. Firstly, calculating the feature vector. This value will be given to artificial neural network for testing. The artificial neural network will decide upon the feature vector input and recognize characters from the number plate successfully. Neural networks are very sophisticated modeling techniques capable of modeling extremely complex functions. In particular, neural networks are nonlinear. The output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges have a *weight* that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Different layers may perform different transformations on their inputs. Signals travel from input layer to output layer after traversing the layers multiple times. The data structures and functionality of neural nets are designed to simulate associative memory. If a feedback loop is provided to the neural net about the accuracy of its predictions, it continues to refine its associations, resulting in an ever-increasing level of accuracy. ANN combining both memorization and generalization. They may be used for classification, regression and association or clustering. To model artificial neurons, the basic nodes in the brain, they developed the concept of perceptron, and to model the connections between them, they made use of signals. A perceptron is a quite simple mathematical function that provides an output value from an input one through a series of computations. The training set was created from the license plate database that was used for plate localization. Regularization, number of training steps and number of hidden layers for the network can impact the performance of the neural network. After training a neural network for varying the regularization parameter λ, it is possible to get the neural network to perfectly fit the training set. It is a case of high variance which means the stability of the network to respond to new samples is poor. Applications of artificial neural network includes function approximation, or regression analysis, including time series prediction, fitness approximation and modeling. Classification including pattern and sequence recognition and sequential decision making. Data processing, including filtering, clustering and compression. Robotics, including directing manipulators. Character recognition stage uses a trainable recognition engine based on a neural network. Each character area is divided into 8x16 smaller rectangles. For each rectangle, an average intensity value is calculated and this value fed to one input of the OCR engine. The training is performed exclusively on the simplest possible type of net: one layer, one neuron and though the resulting net is as powerful as a multilayer perceptron. The pattern subsets contain always n-1 correctly classified and one misclassified pattern. No derivatives are calculated and no preprocessing is needed. Redundancy elimination checks are performed and the redundant units are eliminated during the training.

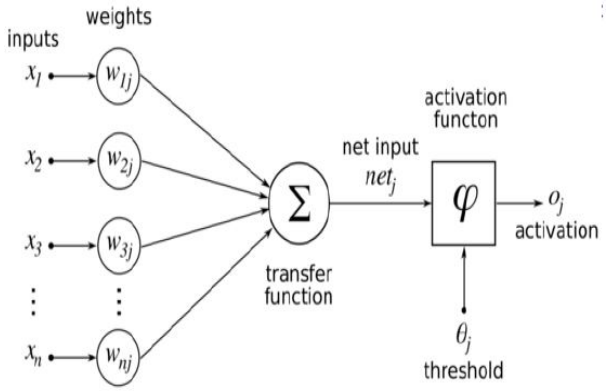

Fig.12 Structure of ANN

3) *Multilayer Perceptron:* The most common neural network model is the multilayer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent). As the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer. Finally, the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output. A graphical representation of an MLP is shown below.

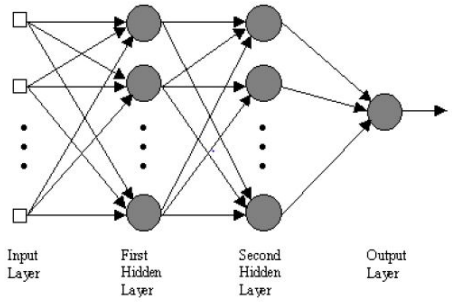

Fig.13 Block diagram of MLP

4) *Feed-forward neural network:* The neural network is defined as an oriented graph G = (N,E) , where N is a nonempty set of neurons, and E is a set of oriented connections between neurons. The connection e(n,n,)∈E is a binary relation between two neurons n and n,. The set of all neurons N is composed of disjunctive sets N0, N1 ,N2where Ni is a set of all neurons from the ith layer.

$$N=N0 \cup N1 \cup N2$$

Numbers of neurons for the input (0), hidden (1) and output (2) layer are denoted as m, n, o such as m =|N0|, n = |N1| and o = |N2| . The number of neurons in the input layer (m) is equal to a length of an input pattern x in order that each value of the pattern is dedicated to one neuron. Neurons in the input layer do not perform any computation function, but they only distribute values of an input pattern to neurons in the hidden layer. Because of this, the input layer neuron has only one input directly mapped into multiple outputs. Because of this, the threshold value of the input layer neuron is equal to zero, and the weights of inputs are equal to one. The number of neurons in the hidden layer (*n*) is scalable, but it affects the recognition abilities of a neural network at a whole. Too few neurons in the hidden layer causes that the neural network would not be able to learn new patterns. Too many neurons cause network to be overlearned, so it will not be able to generalize unknown patterns as well. The information in a feed-forward neural network is propagated from lower layers to upper layers by one-way connections. There are connections only between adjacent layers, thus feedforward neural network does not contain feedback connections, or connections between arbitrary two layers. There is no connections between neurons from the same layer.

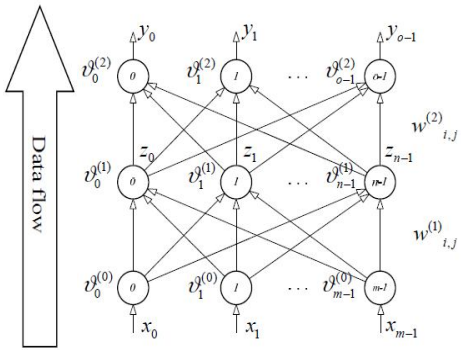

Fig.14 Architecture of the three layer feed-forward neural network.

The system is tested by using videos which taken by a static HR digital camera. Here we evaluating background subtraction effectiveness and the automatic number plate recognition techniques. The foreground estimation is developed by a Low Rank and Structured sparse decomposition method which gives better accuracy and less affected by background noises. Any car should be considered foreground, but the stationary objects are missed due to the lack of motion.

The ANPR system works on the basis of histogram manipulation and morphological operations. The wrong identification came from the fixed screws on the plate that was recognized as zeros, and if the distance between the camera and car was larger than certain limit or major slant on the plate. If the background of the plate was not white the contrast of characters has been poor. There is possible of many problems in shadowed regions but we solved by concentrate the illumination to the car region.

In background subtraction we compared LSD with the following approaches. Original PCP uses l1-norm, LBD employs the l2,1-norm for block-sparse constraint, and DECOLOR uses the MRF smoothness constraint. The algorithm LBD using the l2,1-norm outperforms the PCP, the reason being that LBD enforces the low-rankness of the background part and the block-sparsity of the foreground part.

From the input video of the two cars we get the background subtracted videos. The number plate localization image can be captured by using a threshold value of area. It captures the image if the predefined value is reached. Here a range of 11×18 (cm) image is capturing and the detected image is displayed as shown in fig. 15

Fig. 15 Grey scale image and binary image of car 1 and car2

By the background subtraction we can easily understand the movements in a particular area. The number of vehicle passed is also counted and predicted how many vehicle passed. After this we get the input image to the RGB to gray conversion in the pre-processing stage. The grey image is given to another stages such as noise removal, sharpening, contrast enhancement and filtering. The gray scale image convertin to binary image as shown in fig: 18. In the edge detecion stage sobel edge detection is used.

Two types of processing take place in morphological processing that localizes the license plate from the vehicle at an efficiency of 83%, at the rate of 0.7 seconds. Whereas, edge processing technique localizes the license plate at an efficiency of 100% and at the rate of 0.15 seconds. The results are presented in Table I

TABLE I
License Plate Localization Efficiency

Method	% of number plate localization	Efficiency (%)
Morphological Processing	87	83
Horizontal and vertical edge processing	100	100

In the number plate localization, the required number plate region is extracted. Horizontal and vertical image projection is used by the histogram equalization. The localized images of car 1 and 2 is shown in fig. 16

Fig.16 Number plate localization of car 1 and car2

The comparison table of the three previous methods with the proposed vehicle motion detection and number plate recognition system is given in table II

TABLE II. Comparison Of Proposed Method With Other Methods

Method	Error detection %	Success %
Proposed method	5%	97%
[5]	6%	92%
[6]	11%	90%
[7]	7%	90%

It has been observed that the system takes about a second to detect number plate from image of size 492 × 874. By using the artificial neural network we got a proper and more accurate number plate detection. The GUI of number plate recognition of car 1 and car 2 is shown in fig. 17

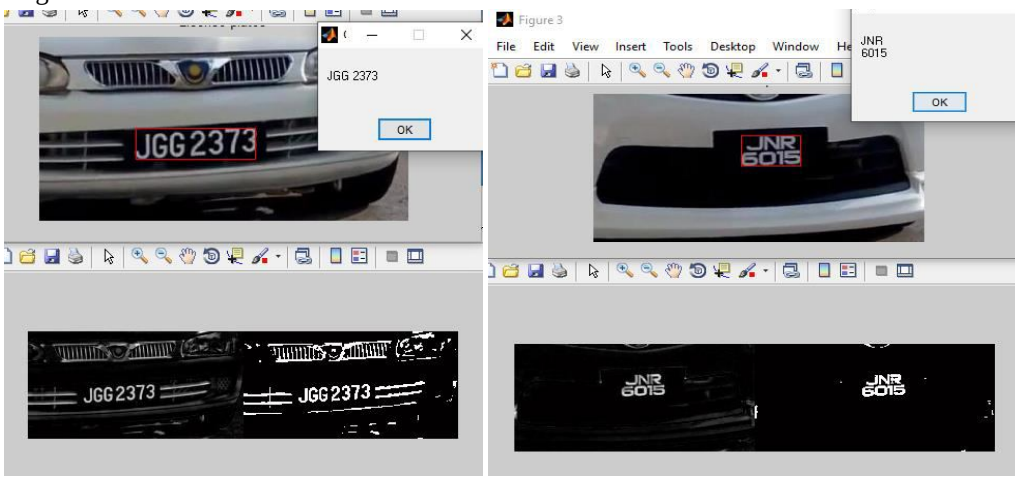

Fig. 17 GUI of Number plate recognition of car1 and car 2

V. CONCLUSIONS

In this project, an effective approach to detect the number plate and motion detection of vehicle in security places is carried out. In the security places detection and counting of vehicle is very necessary. Thus, a background subtraction technique using low rank and structured sparse decomposition is using. Here the matrix is decomposing into a low rank one and a group sparsity one. And then the number plate recognition system is done using morphological operations and histogram manipulations. It detected the number plate more efficiently. The low rank and group sparsity constraints make the model robust to noise and handle diverse types of videos. The algorithm using artificial neural network helps to process the system in most of the challenging situations. Furthermore, the system can utilize any existing traffic surveillance infrastructure without further modification or tuning. Sets of blurry and skewed snapshots give worse recognition rates than a set of snapshots which has been captured clearly. The proposed has reduced computational cost and providing more accurate results for various different kinds of number plates. The system works well either in real time mode or in already stored videos. In the future work we can modify the algorithms to detect the double row plates. The system can also modify in order to detect far number plate and also in high speed vehicles

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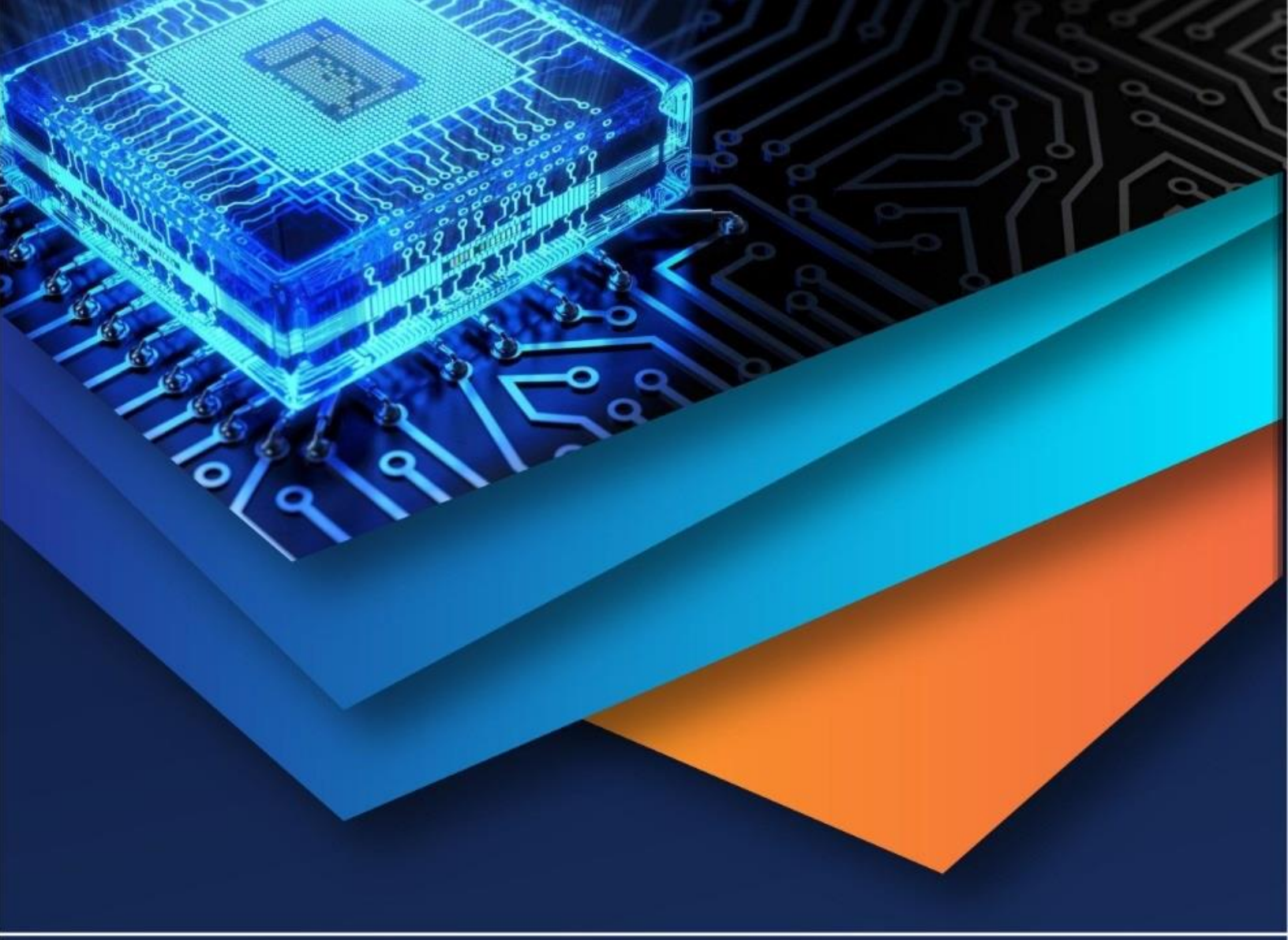

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