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An Efficient Methodology of Automatic Vehicle Number Plate Detection Using Deep Learning

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Abstract: Using advanced computer vision techniques, Vehicle Number Recognition (VNR) can determine a vehicle's unique identifier in real-time video. An efficient Vehicle Number Recognition System will be developed and implemented to facilitate the automated collection of toll taxes. The device will first try to determine what kind of automobile it is before snapping a photo of the front of the vehicle. Localization and partitioning of characters on a vehicle's license plate. The system works best with monochrome images, but it can still decipher the license plate's color. The effectiveness of the system is evaluated using real-world photos and videos once it has been constructed and simulated using deep learning and other technologies. Additionally, the vehicle data (including the date, time, and toll amount) is tracked by the database. Features have been extracted and classified using deep learning. For experimental analysis, we employed both synthetic datasets and real-time photographs of car registration numbers. Data Acquisition and pre-processing methods including color space conversion, cropping, filtering for noise reduction and enhancement are all carried out using the suggested framework. The histogram segmentation technique of picture segmentation is carried out via several feature extraction selection strategies. Classification in deep learning is used to address issues with many hidden layers and unique optimization strategies. Ultimately, the system's effectiveness is demonstrated by contrasting the suggested system with other cutting-edge techniques and algorithms. The outcomes of the trial demonstrate that the system's design can correctly recognize an automobile's license plate in both stationary and moving images.

Keywords *– ANPR, Character Segmentation, Convolutional Neural Networks, Edge Detection, License Plate Extraction, Morphology, OCR.*

1. Introduction

The primary purpose of optical character recognition (OCR) technology is to identify text that has been handwritten or produced by machines in scanned documents or photos and then transform it into an editable format. OCR can be used to create computer-guided traffic systems, which are intelligent traffic systems that operate mostly without human assistance. Intelligent traffic systems will heavily rely on number plate identification. The primary issue posed by the growing number of cars is traffic control, as is the growing volume of vehicle data that must be analyzed to check for violations of traffic laws or stolen vehicles. Consequently, it's critical to have a system that lessens the workload for human operators. This technology allows us to recognize and keep track of different car number plates in a database. The technique employed for the project had identified the security risk associated with tracking multiple car numbers at the campus entrance. The user may occasionally be unable to collect data for a variety of reasons, including poor vision, light conditions, poor interpretation, and the inability to record data when there are numerous buses present in a situation. This might not seem like a big deal, but if data is not collected at gateways under strict observation and with good security, it could cause some major security problems. In order to prevent these kinds of situations, we create a module that recognizes the license plate of cars that are going through the gate. Utilizing a module-based algorithm that recognizes the cars and takes pictures of their license plates. Moreover, it automatically enters and records arriving and exiting vehicle information into the database without the need for manual labor. By using this model, we can save correct vehicle data, prevent manipulations, and record it in a database.

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A. Motivation:

- After identifying various existing system research bugs we introduce a new system with below features
- Our project's primary goal is to automate traffic control at toll plazas while making little changes to the current system, which should also result in a lower cost.
- By controlling human intervention through this system, we can reduce the likelihood of corruption, provide faster and more efficient service—for example, by eliminating the need for manual toll charge exchanges—and send messages in place of receipts for notifications.

B. System overview:

The base system uses a simple automatic number plate recognition (ANPR) technique that may be used to many different automated vehicle number plate identification scenarios. Its goal is to aid in vehicle number plate recognition by applying a simple algorithm to camera images. The five components that comprise the number plate algorithm are image acquisition, pre-processing, edge detection and segmentation, extraction function, and number plate character identification using suitable machine learning techniques.

To create an automated system for toll plaza number plate recognition using deep learning (DL) and the Internet of Things. The left and right camera sensors at the site where the system is initially installed are used to continuously record VDO steaming for departing vehicles. Subsequently, the data is transformed into various image frames and sent to CNN. CNN extracts the vehicle type information from the master cloud database and determines whether the image has a number. It automatically prepares the appropriate tax bill for each type of car and sends it to the transaction web server.

A state-of-the-art technique called vehicle number plate recognition (VNPR) reads and recognizes vehicle registration plates using optical character recognition (OCR). Law enforcement, parking management, toll collecting, and traffic monitoring are just a few of the many uses for it. In most cases, the system is made up of multiple essential parts:

- *Camera System:* Vehicles and their license plates are photographed using high-resolution cameras. The best visibility and image quality can be achieved by carefully positioning these cameras.
- *Image Preprocessing:* This stage entails editing and enhancing the taken pictures to raise the quality of the license plate in preparation for additional processing. This can involve tasks like contrast adjustment, noise reduction, and image scaling.
- *Character Segmentation:* To separate and identify each character for recognition, the characters on the number plate are separated from the surrounding image. This is an important step, particularly when working with various character sizes, styles, and fonts.
- *Optical Character Recognition (OCR):* This is the main part of the system that recognizes the characters on the divided license plate. The segmented characters are interpreted and transformed into machine-readable text using OCR methods.
- *Database and Matching:* The recognized text is compared against a database of registered vehicles or a list of vehicles of interest. This allows for quick identification and retrieval of information related to the identified vehicle, such as owner details, registration status, and any associated records.
- *Alerts and Actions:* Based on the matched information, the system can trigger specific actions, such as generating alerts for law enforcement purposes, enabling access for authorized vehicles, or initiating billing processes for toll collection or parking management.
- *Integration with Other Systems:* VNPR systems can be integrated with other surveillance or security systems to enhance the overall efficiency and effectiveness of traffic monitoring, security enforcement, and crime prevention.

1) Applications:

- Deep learning and Internet of Things applications for automatic number plate recognition.
- Two examples of this are automatic parking systems and toll tax systems that recognize license plates.

2) Advantage:

- Reducing wait times at the tollgate by eliminating the need to stop vehicles and requiring manual transactions.
- The textual features produce accurate results and lower the rate of errors.
- Automated toll collection reduces traffic congestion and minimizes delays for commuters, making the overall traffic flow more efficient.
- The system can provide valuable data for traffic analysis, allowing authorities to make informed decisions about road maintenance, upgrades, and traffic management.

3) Disadvantage:

- Implementing a VNPR system requires a significant upfront investment in cameras, sensors, software, and infrastructure.
- The system relies on a stable internet or cellular data connection for real-time communication, which may not be available in remote areas.

2. Literature Review

A. Background:

Toll collection is currently done manually. It is time-consuming since it takes time to collect the toll amount. Because this approach takes a long time, it pollutes the environment and wastes fuel and money. An automated coin machine is an additional technique, although it takes a lot of time. Another technique that is now in use is prepared card toll collection, which saves time and has certain management benefits but lacks security because anybody can use the card. Therefore, we must develop a more sophisticated automated toll collection system as a solution in order to address the shortcomings of the current ones.

B. Literature Survey:

Absolutely, let's dive deeper into each citation:

According to [1] this study emphasizes the enhancement of Optical Character Recognition (OCR) accuracy by employing Convolutional Neural Networks (CNNs) subsequent to using the YOLO V3 model for detecting the Region of Interest (ROI). The approach involves a sequence of techniques, such as Weiner filtering to deblur images, ROI calculation using YOLO V3, segmentation to refine photos, and the application of CNNs for OCR purposes. Additionally, a dataset containing 6439 images of alphanumeric characters in the Indian Number Plates Font was created, contributing to improving the dataset's suitability for entering into the CNN model.

According to [2] this comprehensive evaluation encompasses various stages of license plate recognition systems. It includes steps like image capture, area detection, character segmentation, and database comparison, leveraging a diverse array of image processing techniques. The paper scrutinizes multiple methodologies aimed at developing efficient license plate reading systems.

According to [3] these methods are tailored specifically for scenarios involving moving vehicles and unattended license plate monitoring.

As Stated in [4] proposes a digital toll management system that not only collects initial toll payments but also integrates driver and vehicle information into a structured data table. The primary goal is to alleviate challenges within toll systems, providing a foundation for smoother operations.

As stated in [5] this study provides an in-depth analysis of Automatic Number Plate Recognition (ANPR) systems, highlighting challenges like plate condition, scene complexity, and camera quality. It suggests potential solutions involving the integration of ANPR with Internet of Things (IoT) and Radio-Frequency Identification (RFID) systems for increased accuracy and efficiency.

According to [6] this research, the Indian government recommends the utilization of YOLOv3, particularly for automated vehicle recognition at toll plazas and urban environments. This adoption is anticipated to contribute significantly to advancements in smart mobility systems.

As [7] discusses the methodology behind license plate readers, emphasizing the utilization of digital cameras and advanced techniques involving Convolutional Neural Networks (CNNs) for image enhancement and character recognition.

According to [8] focused on Machine Learning-based auto towing management, this study introduces algorithms designed to precisely locate license plates on vehicles. The process involves generating grayscale images from retrieved bounding boxes, identifying boundaries of alphanumeric letters, and utilizing K-Nearest Neighbors (KNN) for accurate number plate determination.

According to [9] introduces models for sensor location and low-cost network architectures tailored for urban mobility planning. These models aim to optimize sensor placements and deploy cost-effective networks as alternatives to traditional methods, such as rubber hoses, commonly used in urban mobility planning.

As stated in [10] this paper delves into the application of morphological operations in efficiently identifying license plates in images. Operations like image enhancement, edge detection using Bilateral Filtering, and template matching for character recognition are explored in detail.

Each study contributes uniquely to the advancement of license plate recognition systems, offering insights and methodologies that collectively aim to improve accuracy, efficiency, and applicability across various domains, from toll management to urban mobility planning.

3. Problem Definitions

The proposed research work on Vehicle Number Plate Recognition using a deep-learning classifier; various features are extracted from users input image data and Locating the number plate of the vehicle. The steaming data is converted into different image frames and passed to a deep learning algorithm**.** We have also compared the proposed methodology to other deep learning techniques.

A. Contribution:

- The majority of the earlier systems had restrictions on how they could operate, such as being limited to specified vehicle dataset matching, motionless backgrounds, interior areas, restricted vehicle speeds, prescribed driveways, or fixed illumination.
- • The primary goal of our study is to develop a reliable number plate recognition model that functions in a variety of lighting conditions and angles.
- System also deals with large scale number plate synthetic dataset.

B. Objectives:

- To study and analysis of Vehicle Number Plate detection using deep learning
- To design and develop various feature extraction and selection techniques for module design.

• To design and develop a deep learning classification algorithm for Vehicle Number Plate detecting.

• To validate the effectiveness of proposed techniques with various image dataset.

C. Observations:

- A lot of researchers have extracted characters from photos by combining machine learning approaches with image processing.
- Due to an unbalanced image data set and an unstable environment for object capture, numerous systems continue to have problems detecting characters.
- The Google deep learning module's optical character recognition (OCR) library, which offers accurate data classification and detection from heterogeneous characters.

D. Overview of Deep learning:

Due to the rapid adoption of IT, automobiles are now included as analytical tools in information systems for many aspects of the modern environment. Detecting and recognizing vehicle license plates is categorized as a smart gadget. Vehicle information must be updated between reality and the information system because an autonomous information system without data is illogical. This can be done by human agents or by specialized intelligent technology.

Plate identification is the final stage of the OCR component of the proposed system. The car plate that was recognized in the prior CNN serves as the source of the CNN data for plate recognition. The network design recommended in the study has been applied to this specific character recognition technique, with slight adjustments made to match the Serb standard in plate character recognition, where the suggested system was tested. Several neurons in the network output layer used in this article are represented by a variety of characters, Including numerals, small letters, and capital letters. Tensor flow's improved device compatibility led to the incorporation of CNN for plate recognition.

E. Mathematical Model:

Let S represent the suggested system that has the following characteristics.

S= {{Iset}, {Ex, Fs, Tr_dataset, Ts_Dataset, Inputcs, $Input_{tp,}$ $Input_r$}, {R}}

which is denoted by =,

Iset -> Gathered data for testing and training. You download the dataset from Kaggle.

Ex-> Triplets' document metadata is extracted.

Fs ->Extract the normalized features set, or features set, from the training dataset.

Tr_dataset → Training data Set

Ts_Dataset → Test data Set

$Input_{cs}$-> Compute the similarity weight using

the suggested deep learning algorithm. Utilizing

an optimization technique,

$Input_{tp}$ -> sorted the best result based on the

weight that was attained.

R ->Predicting the vehicle number based on the

available category.

Condition:

1: If the Vehicle Number data score is high, it is Vehicle Number Recognition detection

0: If the Vehicle Number data score is less, it is Vehicle Number Recognition not detection.

Explanation:

Let S, be the proposed system which is characterized as below:

S= {{Iset}, {Ex and Fs, Tr_dataset, Ts_Dataset and $Input_{cs,}$ $Anylsis_{aa}$}, {R}}

which is denoted by =,

Iset -> Gathered data for testing and training. You download the dataset from Kaggle.

There are 1080 photos total in this collection, which includes both grayscale and color photos that were shot from the front, back, and various angles of the car. Make training, validation, and test sets out of your dataset.

Thirty percent is set aside for testing and seventy percent for instruction. We get information from synthetic or real-time automobile images combined with license plates. These kinds of photos are also gathered from social media platforms like Flickr and Google Images.

Ex and Fs → Take a look at the normalized features set that you extracted from the training dataset.

To effectively categorize segmented regions into exudate and non-exudate, it is crucial to capture pertinent and distinctive features that optimize their class distinguishability. It is imperative to address false positives, such as light reflections and, notably, optic discs. The automation of optic disc localization, as outlined in the aforementioned methods, becomes pivotal. Distinguishing the segmented regions involves leveraging features like color, size, edge characteristics, and texture.

Tr_dataset → Pre-trained data Set

Train your model with the training dataset, employing an appropriate loss function such as categorical cross-entropy. Utilize an optimization algorithm to minimize this loss, while actively monitoring the model's performance on the validation set to guard against overfitting. This trained model serves as the foundational classifier for feature extraction, contributing to the supervised learning of the system's Background Knowledge (BK). In the refinement process, we have implemented a CNN as the core architecture for the proposed new classifier.

Ts_Dataset and Input$_{cs}$→

Evaluate the test dataset by implementing the proposed deep learning algorithm and compute the similarity weight. Opt for the selected Vehicle Number Recognition classification algorithm in deep learning, feed the training corpus into the classifier to generate a training model, and optimize the results using an optimization algorithm to prioritize the most effective outcomes based on achieved weights. Once the training model is obtained, input the testing data to obtain classification predictions. The testing phase involves preprocessing the testing text and classifying it based on the trained model.

Anylsis$_{aa}$ → Evaluate the accuracy using confusion matrix evaluate the performance analysis of system.

R → Vehicle Number prediction based on available category

Condition:

1: If the Vehicle Number data score is high, it is Vehicle Number Recognition detection

0: If the Vehicle Number data score is less, it is Vehicle Number Recognition not detection

4. Proposed System

The presented algorithm proves highly effective in extracting information from Indian license plates. It exhibits robustness in handling skewed, inadequately illuminated, or atypically formatted number plates. Employing contour extraction through border following, we apply filters based on character dimensions and spatial localization before initiating the segmentation of number plates. Various image processing techniques are incorporated, including Sobel edge detection, Gaussian thresholding, morphological modification, and Gaussian smoothing. The retrieved characters are subsequently decoded using Optical Character Recognition (OCR). Once identified, the texts are organized, cataloged, and integrated into a searchable database for easy retrieval and reference.

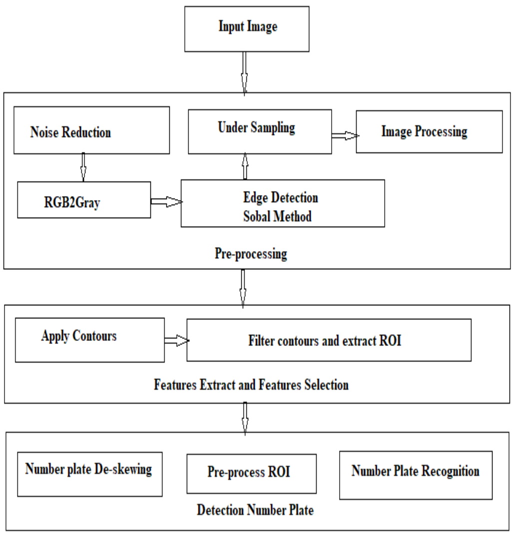

Fig 1: Proposed system architecture

• A basic method for the Automated Number Plate Recognition (ANPR) System is included in the base system. This technology has numerous applications for the automated recognition of vehicle number plates.

• Using camera images, a basic algorithm is created to assist in the recognition of vehicle number plates.

• There are five components to the algorithm for number plate recognition: picture acquisition, pre-processing, edge detection and segmentation, feature extraction, and character recognition of number plates utilizing appropriate Deep Learning algorithms.

A. Image processing:

An essential first step in every image analysis system is image pre-processing. Inadequate pre-processing will render the recognition useless or possibly lead to inaccurate outcomes in subsequent phases. Improving the quality of the image that will be processed for recognition is the primary goal of pre-processing. We're going to use a few different techniques, like noise reduction, image binarization, and RGB to grayscale conversion.

B. Noise Reduction:

Image noises are distortions in the image that occur from camera malfunctions or from changeable weather-related low visibility. The pixel intensity levels' random variation is also referred to as noise. There are many different kinds of noise, including salt and pepper and Gaussian noise. We remove noise using an iterative bilateral filter in this proposed method. Compared to a median filter, it preserves edges better and offers a mechanism for noise reduction.

C. Binarization:

The technique of binarizing a picture results in an image with only two pixel values, or black and white pixels. Since edges in binary images are more clearly defined, completing the binarization procedure before detecting and extracting the license plate from the image will facilitate the process of license plate detection. The process of binarization involves choosing a threshold value. We examine the image's pixel values after deciding on a value. Should the value exceed the threshold, the pixel in question should be entirely black or white. By choosing a global threshold value, this straightforward thresholding procedure might not produce the desired results. In order to get around this, we employ an adaptive thresholding technique, which determines the threshold of a smaller region in the image that produces better results rather than choosing a global threshold value.

D. Number Plate Detection:

When extracting license plates from images, it's critical to consider the plate's limits. We have a variety of techniques for doing this, including the Hough's Line and Sobel's edge detection techniques. By grouping the places where the shapes cross, the linked component technique now assists us in determining the true nature of the shape. We can determine whether a shape is a rectangle or not by obtaining the intersection points of the shapes and calculating the number of points in each group. Now that we have the points of the rectangles, we can effectively extract the rectangular portions of the image, and from there, we can obtain the license plate based on the major and minor axis lengths, area, bounding box, and other features of the license plate. As of right now, the retrieved plate is just an inverted binary representation of the car taken from the original image. Such an image cannot be subjected to further actions. To prepare the image for further processing, we transform it to a binary image.

System Flow Diagram

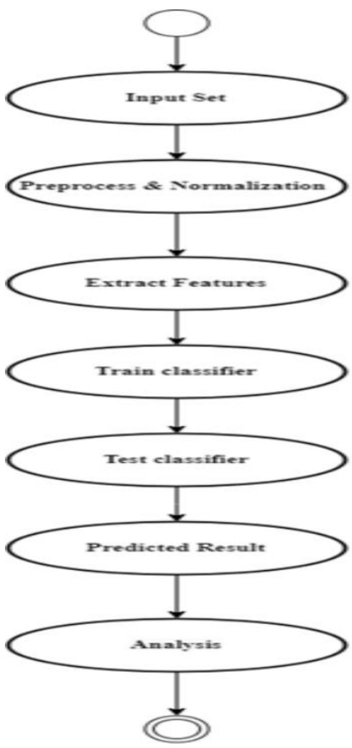

Fig. 2. System Flow Diagrams

5. Implementation and Experimental Analysis

A. Implementation:

A basic method for the Automated Number Plate Recognition (ANPR) System is included in the base system.

This technology has numerous applications for the automated recognition of vehicle number plates.

- Using camera images, a basic algorithm is created to assist in the recognition of vehicle number plates.
- There are five components to the algorithm for number plate recognition: picture acquisition, pre-processing, edge detection and segmentation, feature extraction, and character recognition of number plates utilizing appropriate Deep Learning algorithms.
- To create an automated system for the toll plaza that uses an Internet of Things (IoT) and Deep Learning (DL) method to recognize incoming vehicle license plates.
- At first, the system uses a left and right camera sensor to continuously record the VDO steaming of departing automobiles.
- The streaming data is transformed into various image frames before being sent to CNN.
- Implement a deep learning system using DCNN. The system will first read the input image and preprocess it using the imageNet Library. Next, using an OCR library, optical character recognition is used to extract each character from the input image. Create a model that can be tested using DCNN and trained using various training images that have the highest number of data points. The system then uses the acquired vehicle id number to obtain all metadata from the master table, including car details, owner information, and outstanding debts. The details below demonstrate the whole execution.

1) **Data Collection:** We collect data has been collected from real time car image or synthetic data along with number plates. We also collect such kind of images from social media such as Google Images and Flickr.

2) **Classifier Step:**

The classification process involves the following steps in both training and testing phases:

a) Step 1: Utilize the VGG Net Model as the foundational Deep Learning Framework and leverage the

Pre-Trained VGG Model.

b) Step 2: Capture and store activations from the second-to-last fully connected layer of the network as feature vectors.

c) Step 3: Train the system using a Convolutional Neural Network (CNN) classifier for each emotion category.

d) Step 4: During the testing phase, determine the predicted category label for each test image by identifying the maximum score among the CNNs.

3) **Analysis:**

We showcase the accuracy of the proposed system and conduct a comprehensive evaluation, comparing its performance with existing systems.

B. CNN Algorithm Details:

The Propose Algorithm Describe in the Below Layers:

1) **Input Layer:**

• The input layer is implicit in the first Conv2D layer.

• In this layer, input_shape=(28, 28, 3) indicates that the model expects input images of size 28x28 pixels with three color channels (RGB).

2) **Hidden Layer:**

The Conv2D layers, MaxPooling2D layer, Dropout layer and Flatten layer collectively form the hidden layers:

• Conv2D layers: These are convolutional layers that learn features from the input images.

• MaxPooling2D layer: It reduces the spatial dimensions of the input, helping to reduce computation and control overfitting.

• Dropout layer: It randomly drops a fraction of input units during training to prevent overfitting.

• Flatten layer: It converts the output of the previous layer to a one-dimensional array for the subsequent Dense layers.

3) **Output Layer:**

• This Dense layer with 36 neurons and softmax activation represents the output layer.

• The 36 neurons correspond to the possible classes (characters) that the model can predict.

• The softmax activation function is used for multi-class classification, providing probabilities for each class.

The Propose Algorithm Describe in the Below Techniques:

1) Convolution: Convolution is a technique used to extract features from an input image. By employing small squares of input data to learn image attributes, it maintains the spatial link between pixels. Relu typically follows it.

• Mathematical Representation:

Conv (X, W) = X*W +b, where X is the input tensor, W is the filter (weight), b is the bias term and * denotes the convolution operation.

2) Relu: The feature map's negative pixel values are all replaced with zeros by an element-by-element procedure. Its goal is to give a convolution network non-linearity.

• Mathematical Representation:

ReLU(x) = max (O, x)

3) Pooling: *While retaining significant data, pooling, also known as down sampling, lowers the* *dimensionality of each feature map.*

• Mathematical Representation:

MaxPooling(X) = max (local region of X)

4) Fully-connected layer: The output layer of this multi-layer perceptron uses the SoftMax function. Its goal is to classify the input image into different classes based on training data *by utilizing characteristics from earlier layers.*

The CNN model is made up of these layers combined. A fully connected layer is the last layer.

There are numerous neural network layers in a convolutional neural network (CNN). It is common practice to switch between convolutional and pooling layers, two distinct types of layers. In the network, the depth of each filter increases from left to right. Usually, one or more fully connected layers make up the final step.

• Mathematical Representation:

Dense (X, W, b) = X.W +b, where X is the input tensor, W is the weight matrix, and b is the bias vector.

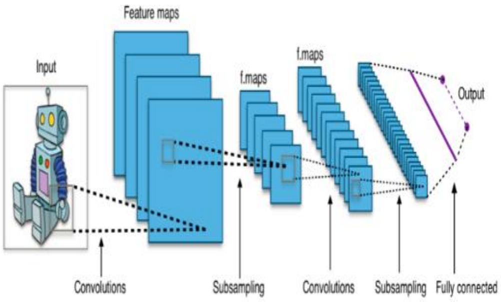

Fig 3: CNN Architecture

1) Input: Test Dataset which contains various test instances TestDBLits [], Train dataset which is built by training phase TrainDBLits [], Threshold Th.

2) Output: HashMap <class_label, Similarity Weight> all instances which weight violates the threshold score.

a) Step 1: For each read each test instances using below equation

$$testFeature(m) = \sum_{m=1}^{n} (.\ featureSet[A[i] \ldots\ldots A[n] \leftarrow \text{TestDBLits})$$

b) Step 2 : Extract each feature as a hot vector or input neuron from $testFeature(m)$ using below equation.

Extracted_FeatureSetx[t……n] = $\sum_{x=1}^{n}$(t) ← $testFeature$ (m)

Extracted_FeatureSetx[t] contains the feature vector of respective domain

c) Step 3: For each read each train instances using below equation

$$trainFeature(m) = \sum_{m=1}^{n} (.\ featureSet[A[i] \ldots\ldots A[n] \leftarrow \text{TrainDBList})$$

d) Step 4 : Extract each feature as a hot vector or input neuron from $testFeature(m)$ using below equation.

Extracted_FeatureSetx[t……n] = $\sum_{x=1}^{n}$(t) ← $testFeature$ (m)

Extracted_FeatureSetx[t] contains the feature vector of respective domain.

e) Step 5: Now map each test feature set to all respective training feature set

$$weight = calcSim\ (\text{FeatureSetx} \mid\mid \sum_{i=1}^{n} \text{FeatureSety[y]})$$

f) Step 6: Return <object_id, weight>

C. Dataset:

- For the first experiment analysis dataset have been used from kaggle.com
- It is basically available in JSON format
- https://www.kaggle.com/dataturks/vehicle-number-plate-detection/data
- Below given image is sample of given dataset which is used for entire research.

D. Experimentation:

The work done in this system can only be judged upon by comparing it with systems that are aiming to achieve a solution to a common end user problem.

Table.1 Comparison of all Existing Systems and Proposed Systems in the literature

Method	Total Samples	Predicted Samples	Accuracy
Automatic License Plate Recognition using Extracted Features [16]	500	424	84.8%
Automatic Vehicle Number Plate Recognition using Structured Elements [17]	150	138	92%
Vehicle Number Plate Recognition System: A Literature Review and Implementation using Template Matching [18]	Unknown	Unknown	80.8%
Automatic Number Plate Recognition by using Matlab [19]	20	18	90.00%
Proposed (OCR+CNN)	105	102	99%

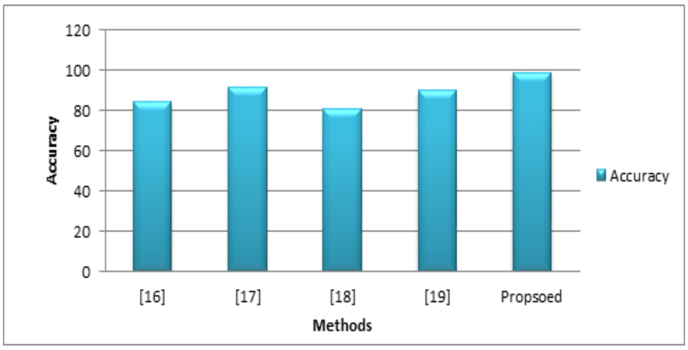

Fig 4: Accuracy of proposed system

E. Result

Fig 5. Input Image

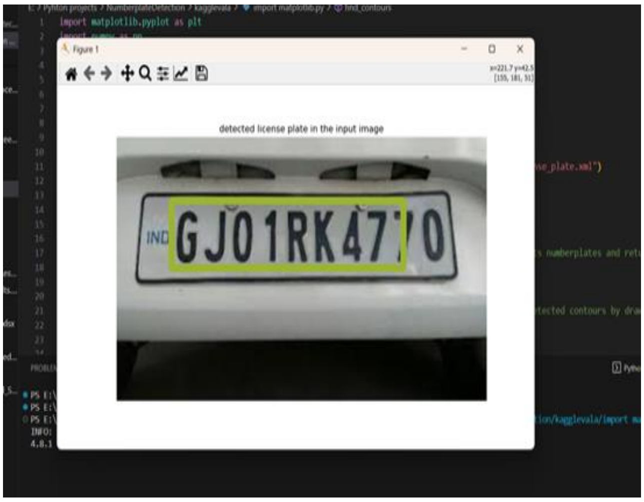

Fig 6. Detect license plate in the input image

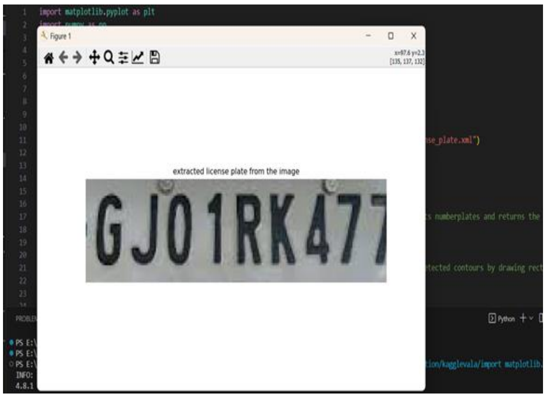

Fig 7. Extract license plate from the image

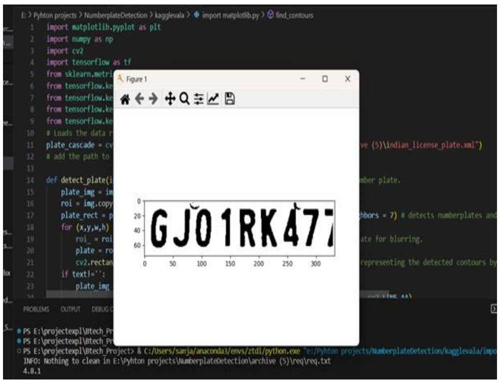

Fig 8. Thresholding of Image

Fig 9. Character Segmentation

6. Conclusion and Future Scope

A. Conclusion

In this paper, an automatic system for recognizing car license plates is described, which is based only on deep learning taught on artificial photos. To address the related issues of plate and character detection, a single deep learning architecture is presented and fine-tuned. Instead of laboriously tagging actual images, the networks are trained using a synthetic dataset. Utilizing a dataset of actual photos, we assess our system. To further assist you, please supply additional context or information. networks of imagery in ambient light. While training the system on only synthetic images, our predicted test results demonstrate that it is possible to achieve precision-recall levels above excellent. There are benefits and drawbacks to each strategy. First, our suggested approach performs pre-processing operations such as noise reduction, image binarization, and RGB to grayscale conversion. Then, using Sobel's edge detection methods, the license plate is recovered. After that, the characters are divided into groups using horizontal scanning. This information is then fed into deep learning to accurately identify each character.

B. Future Work

Our technology deducts the toll amount from the user's wallet automatically as part of the toll payment process. The security system and vehicle parking can both be enhanced with the same concept. In the future, the police should be included in this system to deduct different fines such as those for high-speed motors, drunk drivers, helmet non-wearers, and challans.

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