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# AMLPDS: An Automatic Multi-Regional License Plate Detection System based on EasyOCR and CNN Algorithm

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***ABSTRACT* –Automatic License Plate Recognition (ALPR) System detects License Plate (LP) of a vehicle. The computer vision zone considers ALPR system as a resolved issue. However, the majority of current ALPR research is based on LP from specific countries and employs country-specific data. Therefore, the proposed methodology deals with the LP which will work on the regions in & around India. The algorithm applied in the proposed methodology is Convolution Neural Network (CNN). The proposed methodology comprises three major steps: Firstly, License plate detection which uses Single Shot Detector (SSD) which divides the image into grid cells, with each grid cell being in charge of detecting objects in that area. Secondly, Unified character recognition which uses easyOCR (Optical Character Recognition) has the ability to deal with multi scale and small objects. Finally, Multi–regional layout detection extracts the correct order of the license plate. The dataset is collected from which is "Indian License Plate Dataset". Experiment results outperform the existing mechanisms in terms of time conception accuracy of LP recognition, end to end recognition and average execution time.**

***Keywords: Deep Learning, SSD, Easy OCR, Convolution Neural Network, Multi-regional LP layout.***

## I. INTRODUCTION

Artificial Intelligence is an upcoming technology that gives solutions to the researchers to solve their real-world problems in an efficient way with the accurate results. Modern problems need modern solutions. One of the main category of AI is Deep Learning. Deep learning has proven its efficiency in every aspect. One of the problems is license plate detection. ALPR (automated licence plate recognition) has a wide range of uses, including stolen vehicle identification, car parking management, toll collection system, observing traffic congestion, and so on. Researchers from all over the world have been studying this subject in order to enhance the efficiency of ALPR in real-world scenarios. In a regulated environment, current ALPR algorithms work admirably. When handling with complicated scenes, the performance get suffers. The lack of freely accessible multi-region datasets and different LP formats are to blame for the limited amount of research done on multi-regional ALPR.

Few researchers work states that it is capable of being working on LPs from various regions. But, by examining the maximum of the LPs layout falls into single-line or double-line LP categories and not the both. The researchers have implemented their work using dataset which is capable to work on only single-line LPs and it need some tactics to work well with the double-line LPs. License plate detection, character segmentation, and character recognition are the three most common phases in an ALPR system. The locale of the LP in a given image is determined by License Plate detection phase. Character segmentation is in charge of subdividing individual characters from the observed LP, while character recognition is in charge of categorizing each of subdivided characters. Since the character recognition stage is directly influenced by the first two stages, they are essential for proper ALPR. If the algorithm fails to detect the location of the LP in an input image in the first phase, then the result of the first phase gets affected in the further phases. A few recent papers suggested some deep learning methods to pull out interdependency between the three stages entirely. These approaches, however, are either adapted to function on certain countries which has specific dataset and pattern to recognize only their country LPs. This paper describes a highly accurate ALPR method that can be used on licence plates from a variety of countries.

In this paper, we have come up with the deep multi-regional ALPR solution which comprises of three modules that incorporates deep learning with a multi-regional LP layout detection algorithm. The proposed ALPR system's first stage is LP detection, which is capable of detecting the location of the LP in an input image. The proposed layout detection approach employs an image processing method to derive the correct LP number sequence from multi-regional LPs. It accomplishes this by discriminating between single line and double line LPs. The proposed system of this paper was examined on Indian Vehicle license plates dataset. In terms of efficiency and speed, our methodology outperformed previous works. We have gathered Indian license plate dataset which contains 29 different states. The outcomes demonstrate the efficacy of our algorithm and confirm the ALPR system's applicability to multi-regional LPs.

## II. LITERATURE SURVEY

Baoming Shan [1] has presented a novel approach to licence plate recognition based on text-line construction and multilevel Radial Basis Function Neural Network (RBFNN). The text-line construction outcome and the features of the automobile licence character arrangement would be used to decide the licence plate's location. The multilevel classification RBF neural network is then used to recognise with feature vectors as data, ensuring that the recognition outcome is accurate and meets the Intelligent Transportation Systems' accuracy requirements. The machine struggles to recognise such characters and numbers, such as 2, 0, 7, and others; as a result, the identification rate is smaller than for other characters.

Nureddin A. Abulgasem et al. [2] has used the Radial Basis Function Neural Network in their research. The RBFNN was used to detect and recognize licence plates. It also employs various image pre-processing techniques such as edge detection, image dilation, filtering to improve the image's accuracy. The pre-processed images are used for LP identification after all of these procedures have been completed. But the character recognition from other images filtering procedure can result in incorrect license plate identification. Shishir Kumar et al. [3] are interested in the field of licence plate recognition as well as image processing and computer vision in the creation of an automatic licence plate recognition system for Indian vehicles (ALPRSIV). It includes algorithms that ensure process plate normalisation, as well as character segmentation, normalisation, and recognition processes. All of these approaches achieve machine invariance against image skew homographs and a wide range of plate conditions. The scheme has certain drawbacks, such as creating a dilemma if the number plate includes additional designs or the font of the number plate changes often.

Yi Qing Liu et al. [4] presented a novel Neural Network-based approach to licence plate recognition. The neural network chip is used to identify the number pad. The chip is made up of two modules: a video image processing module and a neural network module that uses a network recognition algorithm and an equalized image processing algorithm. Since the software system is entirely reliant on the PC, some interruption in the PC might result in the failure of any plates. Cons: There is a lower degree of recognition.

Based on morphology and template matching, S. Hamidreza Kasaei et al. [5] has proposed a new real-time and comprehensive method of licence plate identification and recognition. The key step of the method is image isolation, which starts with a visual image captured by a camera in various situations. The image is first pre processed for further identification, and then a morphological operator is used to locate the image. The shapes act as the basis for the morphological operator. For character segmentation, partition scanning is used. The character recognition process is assisted by the template matching process. The picture correlation technique is used in this case. If the accuracy of the picture is poor, the machine would struggle to recognize the characters.

Serkan Ozbay et al. [6] introduced a modern clever and quick algorithm for recognizing licence plates. Plate area extraction, character segmentation, and identification are all aspects of the LPR's operation. Model matching is used to complete the recognition process. After converting the plate to a binarized image, the smearing algorithm is used to determine the plate area.

## III. INFERENCE

From the above reference, Either Single or Double line LP recognition is applicable. Recognizing both the layout is not applicable. Applicable only for particular region, not for multi – regional LPs. Also, the proposed system provides the LP detection between states of India.

## IV. SYSTEM ARCHITECTURE

The Overall System Architecture of an Automatic Multi-regional Licence Plate Detection based on easyOCR and CNN Algorithm is shown in fig.1

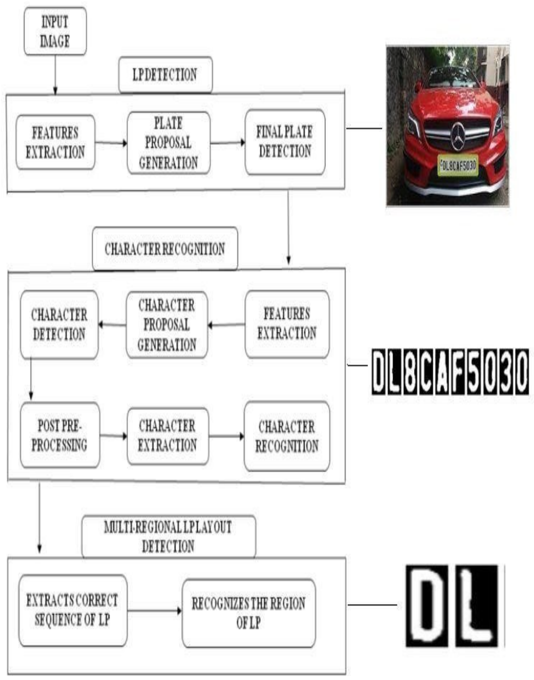



Fig.1.Overall system Architecture of an Automatic Multi-religional License Plate Detection based on easyOCR and CNN algorithm

### *A. LP DETECTION*

The car image is taken as input. The unwanted noise in the input image will be extracted. The algorithm named "Single Shot Multibox" is applied for the object detection. Finally, the layout of the License Plate is detected. The resulted image will be used for subsequent process.

### *B. CHARACTER RECOGNITION*

The car image with the detected LP layout is the input for the next step. The LP layout from the car image has been extracted. Technique called easyOCR is used for further implementation. Character has been spotted from the LP layout. Undergoing training with fewer images, Character has been individually extracted from the detected LP layout. By comparing the trained data, the individual characters are validated and recognized.

### *C. MULTI-REGIONAL LP LAYOUT DETECTION*

The unified characters from the second phase are the inputs. This phase will extract the correct order of the LP. And it finally recognizes the region of the LP.

## V. PROPOSED WORK

This section explains the working of the proposed ALPR solution. Single Shot Multibox is the foundation of proposed scheme. The proposed algorithm's total block diagram is shown below.

1. License Plate Detection.
2. Character Recognition.
3. Multi - regional LP Layout Detection.

## VI. LICENSE PLATE DETECTION

The identification and localization of the LP are dealt with in this stage of the algorithm. This stage's main objective is to limit or constrain the search part for the character recognition phase. The confined LP is critical in lowering the amount of erroneous character detections outside of the LP region. In this point of our system, we consider using the single shot detector. We use single shot detector in particular for this phase of our proposed algorithm. SSD divides the image into grid cells, with each grid cell being in charge of detecting objects in that area. Detecting objects simply involves forecasting the class of object and its position within a specified locale. An SSD is made up of two parts: a backbone pattern and an SSD head. As a feature excerptor, the backbone pattern is generally a pre-trained image classifying system. This is normally a ResNet system trained on ImageNet that has had the final completely linked classification layer removed. While maintaining the spatial structure of the image, although at a lower resolution, deep neural network that can derive semantic meaning from an input image as a result. For an input image, the ResNet34's backbone produces 256 7*7 feature maps. The backbone is represented by the first fewer layers of white boxes in the diagram below, while the SSD head is represented by the last few layers (blue boxes).

Fig.2. Architecture of a CNN with a SSD detector

Multiple prior/anchor boxes can be allocated to each lattice cell in SSD. These anchor boxes are pre-defined, and every individual is in charge of a grid cell's size and shape. During training, SSD make use of a coordinating phase to align the relevant anchor box with the bounding boxes of every ground truth object in a picture. In essence, the anchor box with the greatest overlay with an object which is in charge of determining the class of object and its position. This method is pre- owned to train the grid as well as to predict the detected objects' positions once it has been trained. In practise, an aspect ratio and zoom level are assigned to each anchor box.

SingleShotDetector = SSD (data, grids=[4], zooms=[1.0], proportion=[[1.0, 1.0]])

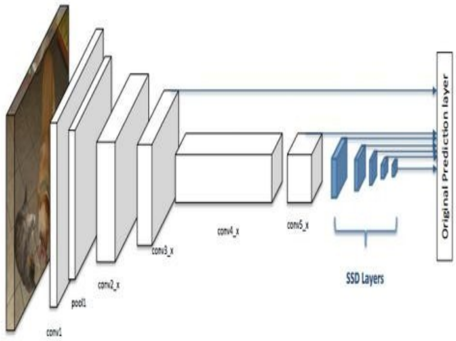
The grids parameter states that the grid cell size, which is 4x4 in this case. In addition, we've set the zoom range to 1.0 and the respective proportion to 1:1. This simply describes that the lattice will build an anchor box for each and every grid cell which is the equivalent size as the grid cell (zoom range of 1.0), square in form, and has a 1.0:1.0 aspect ratio. The outputs propel alongside the depth of the eventual feature map are used to move and range this anchor box (within a fair range) so that it can reach the existing bounding box of the item, even if it doesn't fit precisely.

SSD (single shot detector) significantly improves the speed at which computer vision tasks are completed by removing the bounding boxes method. A convolutional filter is used to depict categories of object in a single shot detection technique, and such filters are used to proliferate feature maps to implement detection on more scales.

### A. *Unified character Recognition*

This stage is in charge of recognizing characters in the LP that was extracted in the previous step. We propose recognizing character as an object recognition problem, in contrast to most previous works, which treat it as a two-step issue (recognition and segmentation). By treating characters as objects, we can combine the character segmentation and recognition steps into one. This stage makes use of easyOCR which is a Python package which converts an image to text.

Optical Character Recognition (OCR) or Optical Character Reader (OCR) is a technique for converting text in graphics into machine-readable text. Printed reports (restaurant bills, invoices, bank statements), placards (sign-boards, traffic symbols), or hand-written text could be used to create these visuals.




Converting these figures to text may be useful for extracting useful data, scanning books and reports and creating PDFs, stocking it in the device, or functioning with it online, such as text to speech (which is particularly useful for visually disabled people), which is commonly used in autonomous vehicles to understand different items.

EasyOCR is by far the most user-friendly OCR solution, with support for above seventy languages, which includes English, Chinese, Japanese, Korean, and Hindi, with more on the way. The Jaided AI Company developed EasyOCR. Since EasyOCR is written in Python and uses the Pytorch deep learning library, a GPU may help fasten the detecting method. The CRAFT algorithm is used for identification, and the CRNN model is used for recognition. Function extraction (we presently use Resnet), sequence labelling (LSTM), and decoding are the three main components (CTC). EasyOCR has few program dependencies and can be accessed directly via its API.

OCR is a new technology that is improving in terms of output accuracy. EasyOCR outperforms tesseract in a number of ways (other OCR engine designed by google make use of python package Pytesseract). It's simple to use and implement, requiring just a fewer lines of code. It's accurate for the majority of photos tested, and it's available in a variety of languages.

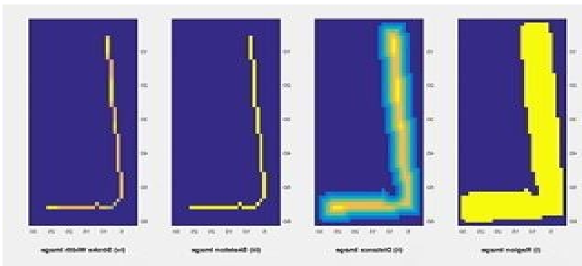


Fig.3. Character Recognition

### B. *Multi-regional LP Layout Detection*

Every regional's record has a distinct layout. Each LP number must be drawn out in the proper sequence. The recognition network's production doesn't include details regarding the LP number's order. As a consequence, heuristics are needed to obtain the final number. The majority of preceding studies have focused on developing methods for determining the exact sequence of a license number. These techniques, however, only operate on the LPs of specific regions and fail when applied to the LPs of other regions. We put forward a methodology for extracting the correct sequence of the LP number in this paper, which is generalizable to multinational LPs.

To construct a all-inclusive algorithm, we must first investigate the pattern of all existing LPs. We look at records from all over the India, from different regions. We discuss LPs from 32 states across India. According to our findings, the majority of LPs worldwide can be categorized as single or double lined licence plates. First, we used xTL n to find all of the known bounding boxes (top left x coordinate). Let b boxes be the ascending-ordered sorted list.

## VII. EXPERIMENTAL ANALYSIS

### *A. DATASET*

The proposed methodology is tested on the dataset containing Indian_licence_plates. Since none of the publicly accessible datasets contained bounding box annotations for LP detection or character recognition, they were manually annotated. The manually collected dataset includes 29 states of India. The proposed approach is trained with 864 images belonging to 36 classes and then it is validated with 216 images belonging to 36 classes. Each image in LP Detection and LP Recognition has resolution of 96*96.

### *B. EXPERIMENT SETUP*

The proposed methodology is trained and tested on Windows 10 system of type 64-bit OS with an Intel(R) Core(TM) i5-7200u CPU @ 2.50 GHz and8.00 GB RAM. The overall system was programmed using python. The platform used for executing the code is Google Colab. Colab is a web-based Python editor that allows everyone to write and run arbitrary Python code. It's particularly useful for machine learning, data analysis, and education.

### *C. PERFORMANCE ANALYSIS*

The proposed methodology is evaluated on Indian License Plate dataset which includes 29 different states to test the effectiveness of our methodology. Our methodology is divided into three sections.

1. License Plate Detection.
2. Character Recognition.
3. Multi–Regional LP Layout Detection.

#### *a) LICENSE PLATE DETECTION*

The License plate is detected from the given input image as shown in fig.4.

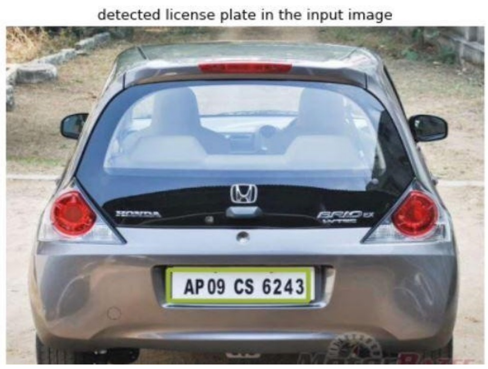



Fig.4. Detected LP

#### *b) EXTRACTED LICENSE PLATE*

In fig.5, the License plate layout alone is cropped and extracted from the detected LP image.

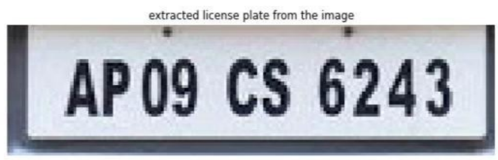



Fig.5. Extracted LP

#### *c) SEGMENTED CHARACTERS*

By using the technique called easyOCR, Character has been spotted from the LP layout as shown in fig.6.

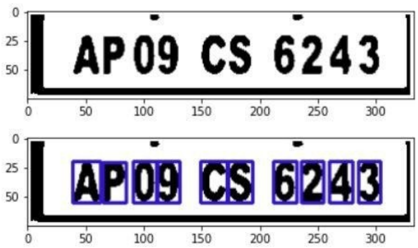



Fig.6 Segmented Characters

### *d) CHARACTER RECOGNITION*

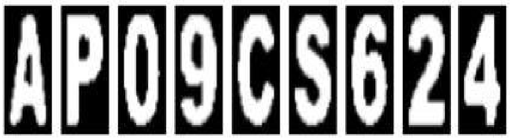



*Fig.7.Character Recognition*

### *e) DISPLAYING THE REGION*

Finally, the region of the License Plate in and around India is found as shown in fig.8.


*Fig.8. Displaying the Region*

## VIII. CONCLUSION

This study has presented an algorithmic strategy for differentiating licence plates of several Indian states. The proposed technique consists of three modules, which have been covered in the previous sections. Character segmentation and recognition are integrated in the LPrecognition problem, which is presented as an object recognition challenge. The proposed method may function on the datasets obtained from many locations throughout India without requiring any extra algorithms or regional-specific features.

## IX. FUTURE SCOPE

The proposed model can be improved so that it can capture images from a wider distance and at a more twisted angle. The AMLPR system should be able predict several licence plates in a single frame.

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