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AUTOMATIC NUMBER PLATE RECOGNITION SYSTEM USINGCONVOLUTIONAL NEURAL NETWORKS

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Abstract: Because of its various real-world uses, Automatic Licence Plate Recognition (ALPR) has been the subject of much study. Unfortunately, a lot of the existing solutions still rely on a lot of limits and aren't strong enough to handle real-world scenarios. This research introduces a cutting-edge ALPR system that makes use of the YOLO object detector, which is both efficient and reliable. Each ALPR stage trains and fine-tunes the Convolutional Neural Networks (CNNs) to make them resilient under varied situations, such as changes in camera, lighting, and backdrop. We provide a two-pronged strategy that uses basic data augmentation techniques, such inverted Licence Plates (LPs) and flipped characters, for character segmentation and recognition in particular.

Keywords: CNN, character recognition,

1. Introduction:

Licence plate recognition provides a wealth of information useful for finding and identifying records. However, the standard procedure for licence plate identification is tedious. Detecting licence plates to recover buried riches of information is not as relevant as manually identifying the vehicle and its owner. There are a number of approaches to building an ANPR architecture, and automatic number plate recognition is a crucial component of an intelligent traffic network [1]. Although there is a strong correlation between the shooting distance and the fraction of the licence plate in the picture, the ANPR architecture [7] is not simple to balance in. On the other hand, the vast open area and clearly discernible licence plate photos make it impossible to catch moving vehicles. Determination is required to discern a licence plate in images that are both small and distorted. Using a CCD camera that can pan, tilt, and zoom (PTZ) is one solution [2]. Each phase has its own set of advantages and disadvantages, and different scholars have suggested different approaches. There are primarily three stages to the process of licence plate recognition. That area is where the extraction is going to take place.

identifying licence plates and personalities.

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Device programme ANPR allows for licence plate recognition. Vehicle licence plates may be seen in camera-captured images. Reading and unfolding licence plates is the main function of ANPR. The acronym ALPR stands for "Automatic Licence Plate Recognition" and describes ANPR as well. This system's software keeps track of licence plates and how they correlate with other data, including time, date, and GPS coordinates. It reads licence plates using optical character recognition technology. An important part of automated parking is LPR. Industry demand for higher-profile commercial parking management projects in smart city zones is likely to drive the inclusion of this functionality. Among its numerous potential applications, it has used as a security measure in toll collecting systems, traffic management, petrol stations and more [8]. Because of its many uses, including highway surveillance, urban logistics, traffic law enforcement, and many more, ITS is a key component in making smart cities a reality [6].

2. Literature Survey:

In this part, we will go over certain protocols that have already been defined.

A lot of effort has been put in over the

on deep learning and image processing techniques for object recognition in the last several years. This area has seen the development of a number of distinct algorithms for vehicle reconnaissance detection and identification. From the literature study, we may see many contemporary strategies in action.

By adhering to a learning methodology, K.K. Kim et al. (2000) constructed a system that could recognise licence plates. Pictured above is the automobile detecting module's interior as seen via the camera. As a result, you will get an image of the potential area. In order to locate the licence plate, the two TDNNs were used as horizontal and vertical filters, respectively. With a recognition rate of and a segmentation rate of 97.5%,

97.2% for the suggested setup [1].

In 2007, Chin-Chuan Han et al. proposed a system that can detect several targets and capture high-quality photographs of licence plate numbers. In order to keep an eye on moving conveyance in an open field, the author has constructed a computer with a tuned dual-camera system. This system consists of a fixed camera and a pan-tilt-zoom camera. In order to recognise the licence plate, a CNN classifier has progressively recognised each one. Data was painstakingly constructed from the scientific photographs, and this method properly discovered 59 IDs, as 64 cars entered this zone

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unlawfully [2].

An ANPR architecture that emphasises convolutional neural networks' learning ability was created by Madhusree Mondal et al. (2017). Because it can differentiate between the vehicle's states based on the licence plate, the self-synthesized feature of CNN was used in this case. In this study, the system was structured as an echelon network of feature detectors that sequentially processed visual input related to the visual cortex's dominant processing experience; this data impacted the CNN's computational model. Although there were fewer training samples used in this study, the results showed a 90% improvement in accuracy [3].

Drawing on the features and variances of the plates therein, Andrew S. Agbemenu et. al. (2018) put up an ANPR approach. In this paper, the author suggests an improved method for use with Ghanaian licence plates in transportation. Two candidate identification algorithms were used in the model's design: one for edge detection and another for algorithm matching the template. In order to eliminate noise, skew, and character arrangement issues, the device used the character segmentation approach, which is especially effective when working with square plates. The tesseract OCR engine was used to produce character recognition at the final point. Feature

Having an average speed of 0.185s identifying 454 plates with 90.8% accuracy, detection was somewhat low but had an excellent success rate. Using optical character recognition, the process took an average of 0.031 seconds and almost 60% of the detected plates were correctly recognised [4].

In their 2018 proposal for an ALPR system, Rayson-Laroca et al. examined the efficacy and reliability of a framework built on the cutting-edge YOLO artefact detector. The CNN are trained and adjusted for each ALPR stage so they can withstand various situations. Using simple data augmentation techniques like inverted licence plates and character returns, the author of this study devised a two-stage approach to explicitly segmenting and identifying characters. Both commercial systems fell short of the 70% recognition threshold, making it impossible to draw any firm conclusions from the UFPR-ALPR dataset. A greater recognition rate of 78.33% was achieved using the suggested technique, but [5].

In order to assist ITS in recognising licence plates from Bangladesh, Prashengit Dhar et al. (2018) created an automated LPR programme. The white backdrop and black lettering on this work plate are quite visible. The detection was carried out by Prewitt operators.

in order to divide the margins of the licence plate. To make the points stand out, morphological dilatation was used. The reconnaissance mission was eventually completed using deep CNN. A remarkable 99.6% accuracy rate was shown by the approach in character categorization [6].

Using Mask-RCNN for multiple oblique pictures and different shooting angles, Cheng-Hung Lin et al. (2019) developed a three-stage method for licence plate identification. In the previous step for vehicle detection, the author used YOLOv2 for the related conveyance. Once we found the licence plate, the next step was to run YOLOv2 once again to identify the plate. At this stage, YOLOv2 divides the 19 × 19 grids that included the pictures of the cars that were recorded in phase I. Finally, character identification was accomplished using Mask R-CNN. In addition to achieving a mAP grade of about 91%, the findings show that the suggested model could categorise car number plates with bevel angles greater than 0-60 degrees [7].

Using convolutional neural networks, NazmusSaif et al. (2019) presented a method to identify Bangla licence plates in car images. The key choice for the proposed system in this study is a convolution neural network due of its

setting up the whole process. In their instance, CNN did far better than traditional image processing algorithms, and when comparing generalised CNN models, CNN models fared better in all of the cases. The YOLOv3 model, which has 53 convolutional layers, was used for the detection investigation. Following identification, the next step is to segment the picture and identify the characters it contains. At this stage, the gadget extracts the licence plate area and passes it on to the second YOLO model for platform picture identification and segmentation. Thus, the model was tested with 200 photos and managed to accurately identify the number plate number in 199 of them, yielding an accuracy rating of 98.5% [8].

3. Methodology:

It is our honest opinion that many ITS uses rely on actual ANPR systems in the real world. Variations in weather and illumination, high vehicle speeds, and poor plate clarity all reduce the effectiveness of automatic number plate recognition systems.

As an example, when it comes to filthy plates, the majority of popular algorithms for plate identification and recognition don't work.

With the right hardware platforms and real-time, resilient, and novel algorithms, this article lays out a system that solves these problems.

When used in real-world web applications, the system can handle a wide range of scenarios, including but not limited to: poor plate clarity, high vehicle speeds, variable ambient conditions, languages, and formats. We are expanding the work utilising hog and CNN to achieve high accuracy and detection for number plate and feature extraxtion. High detection and identification accuracies on dirty plates are the major advantages of our technology.

Two novel data sets were developed and used in this study to accomplish credible assessments: the "Highway Data set" for vehicle counts on highways and the "Crossroad Data set" for violation detection. Our system achieves 98.7% accuracy for plate detection, 99.2% accuracy for character segmentation, and 97.6% accuracy for plate identification on the Crossroad Data set. The detection rate for vehicle counting applications across the Highway data set is 99.1%, while the false alarm rate is 0.5%. Using a publicly accessible English plate data collection, we also evaluated our method and managed to reach an overall accuracy of 97%. Many previously reported ANPR systems are compared to the proposed system from various angles.Practical considerations led to the installation of several ANPR systems at various routes and crossings throughout

Ahvaz, the Iranian capital. After a year of nonstop testing in a variety of weather situations (rain, snow, dust, etc.), these systems have shown to be both sturdy and dependable. Here we outline the specifics of the licence plate recognition system that has been suggested. There are three components to the suggested solution: character detection, licence plate identification, and licence plate detection. These components are shown in Figure 1. We use SSD, a well-known deep learning-based object identification method, for object detection in this work [8]. Results for object identification tests demonstrate that the SSD model outperforms alternatives with respect to both speed and accuracy [11]. The SSD model is able to recognise items of varying sizes since it examines objects in feature maps from different layers. We carry out the region and character identification of licence plates using the SSD object detector, as will be detailed later on. I. Locating Licence Plates Locating the arriving vehicle's licence plate inside the recorded picture is the first step in the licence plate recognition job. In a licence recognition job, the area around the licence plate is the most important part. For the sake of our work, we will disregard the rest of the picture. We use SSD model [8] for licence plate detection operation. The

A training dataset that is annotated with licence places is used to develop the model.

Character Detection

On the detected license plate region, license plate characters are localized with an object detector. In this stage, we compare SSD object detection method with DPM [12], which is an effective model for character detection on license plates as shown in [3]. The trained models can detect 33 different characters; 23English letters (excluding „Q", „W" and „X") and 10 numbers from „0" to „9". Thedetails of these methods are as follows: SSD Model: In this approach, SSD object detector [8] is utilized to detect the characters within the input image. For this operation a character detection SSD model is trained using a character regions annotated training dataset. DPM Model: We utilized a deformable part based character detection model in which each part is a node on the tree (we used 3 nodes in the tree) and mixture model captures the structure of the 33 different characters.

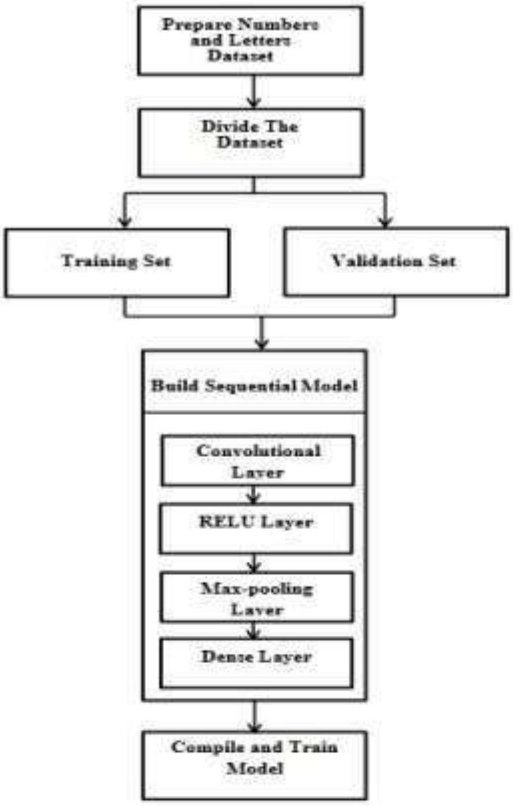
License Plate Recognition

After the character detection task, license plate is recognized. For an accurate recognition, some rules are obtained. The first rule is, the detected character is ordered with respect to their center pixel points. The second rule is, if the detected character region is overlapped withanother detected character region and this overlapping ratio is greater than 70 %, the one with the highest detection score is used as the detected character. The final rule is, the first two and the last two character of the plate should be number. Thus, any letter detected on this range is ignored.

Proposed Block Diagram:

Fig 1 shows the block diagram for the proposed model

Step 1-Prepare Dataset For our project a prepared dataset of numbers and letters to recognize characters on vehicle number plate, which in spite of any environmental conditions and at any capturing angle is stored. Two folders are created,



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A. Training and

B. Validation folder.

A.Training Folder- In training set, total 36 classes and each class contains 800 images for training. Training folder data is on which the neural network works.

B.Validation Folder- Similarly, In validation set total 36 classes and each class containing 200 images for validation. The neural network while learning through the training set also checks the loss from the validation set.

Step 2- Build Sequential Model Build the model using deep neural network library in matlab as backend. We are using sequential object to model our neural network.

Step 3-Compile and train the model We use categorical cross entropy as loss function, because we utilize multi-classification in our project. Adam optimizer is used to reduce the loss function. After training for 10 epochs, our model achieved an accuracy of 98.57 %.

In this study, either a single channel NIR or a three channel RGB image are utilized in the decision making process. Instead of creating different models for two types of image source, we convert single channel NIR images to 3 channel NIR images by cloning them channel-wise and generate a single model using an NIR or an RGB image. Below, we outline procedures and hyper parameter selections for SSD models in license plate detection and character detection stage and for DPM model in the character detection stage. SSD Model: During the training process, we utilized transfer learning approach to make the training process more efficient. We utilize a base SSD model presented. Using this base model, we fine-tuned itwith our specific datasets. Fine tuning operation is performed by freezing the weights of the first three convolutional blocks of the model. The rationale behind this strategy is based on two facts. First three convolutional blocks trained with a large dataset behave as a feature extractor. Thus, there is no need to update these weights with our relatively small dataset. Secondly, since the first feature map to be analyzed to detect objects fall into fourth convolutional block, it is logical to update weights starting from there. In our fine tuning operations, we set the batch size as

16. As learning hyper parameters, Adam optimizer with a relatively small learning rate 0.0003 is utilized. Also we applied learning rate decay strategy shown in Eq. 1 where λ is the learning rate, i is the epoch number.

$\lambda_{i+1} = \lambda_i * 0.9$ ------------------------ (1)

DPM Model: Proposed tree model T = (V, E) is a pictorial structure where V is the set of parts, and E is the set of edges between parts. [14] defined a score for a particular

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configuration of parts L = {li}, for a given image I as shown in Eq. (2), where φ is the histogram of gradients features (for the landmark points) extracted at pixel

$$S(I,L) = \sum_{i \in V} w_i \cdot \varphi(I, l_i) + \sum_{i,j \in E} a_{ij} dx^2 + b_{ij} dy^2 + c_{ij} dx + d_{ij} dy \ ($$

location li = (xi, yi). First term sums the appearance evidence for placing the ith template, wi at location l . Second term score the spatial arrangement of the set of parts L, where dx (dy) term represents the spatial deformation in x (y) axis between parts i and j. This model can be viewed as a linear classifier [15] with unknown parameters w and deformation parameters {a, b, c, d} learned during training using latent classification.illustrates the DPM models obtained for several characters. For a given test image I, we maximize Eq. (3) using dynamic programing to find the best configuration of parts.

$S*\ (I) = maxm\ [maxL(I,\ L)]$ --------------- (3)

4. Results:

Fig 2 Shows the input image

Fig 3 Feature Selection Model For the image

Fig 4 Recognized plate

Fig 5: Extracted Output

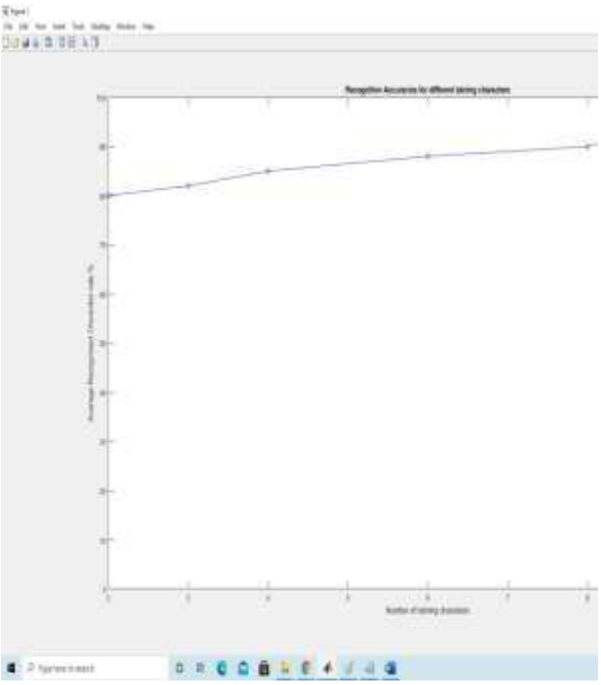

Fig 6: performance analysis

5. Conclusion:

Research on the use of licence plate recognition for traffic monitoring is detailed in this article. For effective traffic surveillance, ANPR is a great and trustworthy tool. Easy detection of interested automobiles from all angles and access to owner information are outputs of a device with a sophisticated image processing technology. When it comes to expanding the smart transport network, ANPR systems are crucial.

There is need for improvement in the numbering system, number plate type (background), moving distance photographs, tilted or side view photos, and image processing techniques when it comes to number plate recognition using neural networks. Neural networks and object detection are great at spotting distant, skewed, or side views, as well as moving photos. In order to achieve excellent accuracies and enhanced accuracy for future recognition, high-resolution cameras with an increased number of frames are being considered for use in possible recognition systems.

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