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MOBILE REGISTRATION NUMBER PLATE RECOGNITION USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Automatic License Plate Recognition (ALPR) for years has remained a persistent topic of research due to numerous practicable applications, especially in the Intelligent Transportation system (ITS). Many currently available solutions are still not robust in various real-world circumstances and often impose constraints like fixed backgrounds and constant distance and camera angles. This paper presents an efficient multi-language repudiate ALPR system based on machine learning. Convolutional Neural Network (CNN) is trained and fine-tuned for the recognition stage to become more dynamic, plaint to diversification of backgrounds. For license plate (LP) detection, a newly released YOLOv5 object detecting framework is used. Data augmentation techniques such as gray scale and rotatation are also used to generate an augmented dataset for the training purpose. This proposed methodology achieved a recognition rate of 92.2%, producing better results than commercially available systems, PlateRecognizer (67%) and OpenALPR (77%). Our experiments validated that the proposed methodology can meet the pressing requirement of real-time analysis in Intelligent Transportation System (ITS).

Index Terms— Intelligent Transportation System (ITS), Optical Character Recognition (OCR), License Plate Recognition, Connected Component Analysis(CCA)

1. INTRODUCTION

Automatic License Plate Recognition (ALPR) emerged as a field of interest and has become an active research domain in recent years. In the modern urban societies, there is a continuous demand to effectuate robust intelligent systems for security and surveillance in the field of transportation, assisting in automatic toll collection [1], traffic law enforcement [2], border control [3], private spaces access control [4] and road traffic monitoring [5]. With the conception to transform cities into smart cities, Intelligent Transport System (ITS) has become an indispensable requirement. ALPR is an integral part of ITS, embedded with complex computer vision processes of image acquisition, object detection [6], segmentation [7], and recognition [8]. So, there is an urgency to make the license plate recognition (LPR) system more dynamic, plaint to the diversification of backgrounds and other environmental factors like illumination, angle, noise, and distortion, which cause a challenge for ALPR. Multiple advanced computer vision technologies and artificial intelligence algorithms have been proposed to identify vehicle licenses in constrained backgrounds [5], [7], [9]. However, in situations of varying backgrounds, these existing systems start to face difficulty in discerning license plates (LP). By using stationary/fixed ALPR Cameras on a bridge and utility poles [10], it is impossible to cover nearly all range of roads, highways, or motorways. Therefore, there is a need to cover the specific unaddressed parts so that the ITS system could become more useful which has become the prerequisite for enacting Smart cities.

Among the existing LPR research, several techniques have been used, such as the cascaded CNNs [1], smearing algorithm [2], morphological based top-hat transformation [11], lightweight fully connected neural network (FCNN) appended with fusion loss [5] and YOLO inspired models [12-14] for plate localization, connected component analysis [7], pixel-based algorithms [3] and projection methods [15], [16] for segmentation and end to end CNN [17], synthetic imaging-based CNN [18] and spatial transformation based CNN [15] for recognition. Most of these plate detection and recognition approaches had a constraint of fixed backgrounds and were trained with license plates having a unilateral language which limits ALPR efficiency as the detection environment gets more dynamic and complex. A meticulous and comprehensive dissection of each part and how they function together is necessary for a successful LPR system. Hence, in this study, we pay more attention to detection and recognition accuracy than time complexity whenever a choice is made.

The main contribution of this paper is the clustering-based multi-language repudiate CNN model for alphanumeric recognition when the license number is in more than one language on LP. This research proves that the proposed model can achieve higher accuracy when trained with a proposed technique, even on a smaller dataset of LP. Our model shows comparatively better results than server-based commercially available LPR systems, [1]OpenALPR and [2]PlateRecognizer in real-time dynamic background scenarios.

The rest of the paper is organized as follows. In Section 2, existing works related to each ALPR stage are discussed. This is followed by presenting the fundamental idea of the proposed LPR methodology in Section 3. Experiment results are presented in Section 4. Concluding remarks and ideas for future work are given in Section 5.

2. RELATED WORK

Several LPR systems have been proposed for LP detection, segmentation, and recognition. Researchers have addressed the LP detection stage by using various object detection techniques. Laroca et al. [1] used two CNN arranged in a cascaded manner to detect car frontal or back-views and LPs, having the lowest false positive rate. Ozbay et al. [2] used a smearing algorithm, a morphological operation on binarized images exclusively for LP detection. Shohei et al. [19] used two-stage YOLOv2 for accurate license plate detection in complex scenes reducing false detection hence improving detection rate. Jain et al. [20] extracted license plate candidates using edge information and geometric properties and then fed them to a CNN classifier for license plate detection. Gou et al. [11] used top-hat transformation, vertical edge detection, and morphological operations for detecting the license plate. Z. Liu et al. [12] used a YOLOv3 detector. It distributes an image into rectangles of S x S(where S is natural number) regions. Each region of algorithm predicts bounding boxes and the class probability. When combine both, give us confidence value. For segmenting alphanumeric, Shen-Zheng et al. [21] applied connected component analysis to segment characters. Wang et al. [16] used a vertical projection method for segmenting characters in which scanning is done left to right until a projection area with a width greater than a predefined threshold is found.

For recognition purpose, Vishal Jain et al. [20] used a CNN-classifier trained for individual characters using spatial transformation network (STN) for character recognition. It performs string recognition on the whole image. Chao Gou et al. [11] used an offline trained pattern classifier based on character-specific extremal regions and restricted Boltzmann machines to recognize characters. It is a probabilistic nonlinear model with a bipartite connectivity graph between hidden units and visible units and describes the distribution of edges in different parts of an image. Serkan Ozbay et al. [2] used statistical-based template matching for recognition alphanumeric where each character is refined and fit to a fixed size so that the matching can be done with the database. Na Duan [14] used an end-to-end CNN using inception structure which utilizes computational resources efficiently and improves the model vertically and horizontally. This also incorporates a deep birth algorithm to make it practical for real-time analysis. Diogo M. F. Barros [18] used a CNN model based on synthetic imaging using Adam optimizer and transfer learning.

3. PROPOSED ALPR APPROACH

In this section first, we describe the process of data acquisition. The dataset contains 20 videos, captured by a camera mounted inside a moving vehicle. We then design a framing algorithm that extracts frames from videos captured. Thus, 1000 frames are extracted and saved in the Portable Network Graphics (PNG) format with a resolution of (1,920 × 1,080), consisting of vehicles. In Saud Arabia, the LPs have size and color variations depending on the type of the vehicle and its category. Cars' LPs have a size of 32cm × 16cm. Private vehicles have white-colored LPs, while other commercial purpose vehicles have blue.

Before designing a learning-based method, we check the effectiveness of existing state of the art Optical Character Recognition (OCR) algorithms. For this, we manually segment the plate and apply morphological operations [2] to prepare a suitable input to the OCR algorithm. The pipeline for this experiment is shown in Fig. 1. The input video gets framed as mentioned above, and in each frame, the number plate is localized manually and converted from RGB to grayscale. The gray scaled image goes to the main morphological processing unit where a flat structural element [2] is defined which is a rectangle of M rows and N columns of size 3x5. Then compound operations [2] of erosion and dilation is applied to reduce small and narrow parts other than LP so that Region of Interest (ROI) becomes more visible. For connected component analysis (CCA), binarization [2] of the image is done which transforms grayscale image in [0 255] range to a binary 0/1 spectrum. Inversion function is used so that alphanumeric in the foreground becomes white and the background becomes black.

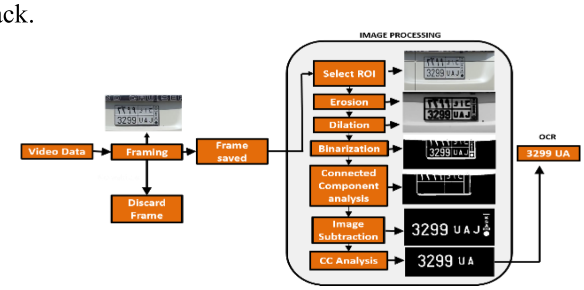

Fig 1: Morphological based OCR for LP recognition pipeline

For better readability. CCA [21] is an important technique that scans and labels the pixels of a binarized image into components based on pixel connectivity with neighboring pixels. This is done to identify the longer components. Next, the CCA processed image is subtracted from the actual binarized image. The CCA is implemented again to remove the coat of arms and the international code KSA letters written vertically at right side of LP. The OCR module is used then to read the text within the processed image.

In our experiments, the overall accuracy of LP recognition through the OCR technique was not up to the mark as it gives

[1]OpenALPR: https://github.com/openalpr/apenalpr
[2]PlateRecognizer: https://platerecognizer.com/

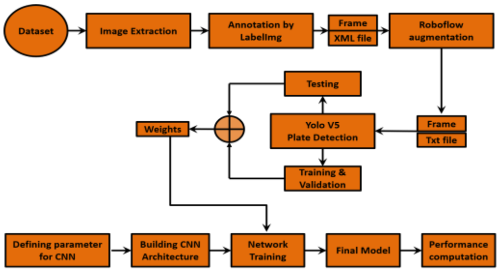

Fig 2: A pipeline for machine learning-based LP recognition.

Fig 3: LP Detection Results

Fig 4: Segmented Classes of Alphanumeric

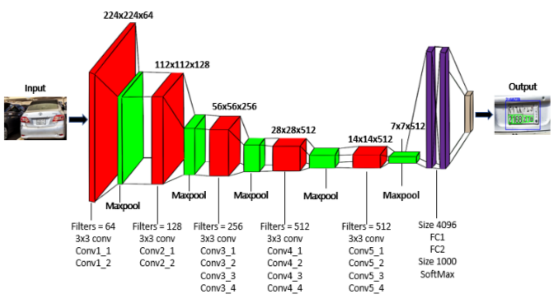

Fig 5: Proposed CNN Architecture

Fig 6: Initial Results

Fig 7: Y-min & Y-max for LP coordinates

s the accuracy of 60% completely read plates, 15% partially read plates and 25% plates go unread. These results show that we cannot achieve good accuracy for LPR in unconstrained real-world situations, where the background changes continuously. For a more accurate and robust approach, it could be better to use a learning-based approach and to let the system learn about different characters and numeric strokes using a large dataset. Our entire pipeline of machine learning-based methodology has been shown in Fig. 2.

The entire dataset was annotated using LabelImg[25], a graphical image annotation tool. For detecting license plates and its alphanumeric characters, YOLOv5 [13] was used which is the best available model for object detection than its predecessors: YOLO [12], YOLOv3 [18], and Faster-RCNN [22] in terms of speed, model storage, and auto anchoring. YOLOv5 uses CSP-Cross Stage Partial Networks[23] as its backbone to extract rich informative features from every input image and PANet[24] as neck to get feature pyramids which makes it faster for detection in real-world scenarios. The annotated dataset was split into 70% training, 20% validation, and 10% testing dataset. We achieved detection accuracy of 98%. Some results of LP detection are shown in Fig 3.

Once the LP is detected, we move towards manual segmentation of the dataset distributed among 36 classes of (0~9) and (A~Z). All Saudi Arabian LPs have the same format: three letters and four digits, we use 26 classes for letters and 10 classes for digits as shown in Fig. 4.
To increase the accuracy of the detection model one should have an ample amount of annotated data to meet the requirement. As our custom Dataset was based on 1000 framed images so different data augmentation techniques are used to generate a more realistic dataset by gray scaling, varying brightness and rotating license plates, and flipping and rotating techniques for digits and characters. This helped us to increase the dataset to 4500 frames and 5000 alphanumeric characters. To recognize the segmented alphanumeric digits and characters efficiently, a convolutional neural network is used with convolution layers at the beginning and fully connected layers at the end. Architecture for our custom CNN pipeline is shown in Fig. 5 where layers are being denoted as;

Conv<number of such filters><size of the filter>

The size of the convolutional kernel is 3*3, and the input size was 224*224*3. We use the alternating structure of multiple convolutional layers and nonlinear activation layers to extract rich features of a given image. The activation function of ReLU with a stride size of 1 pixel for convolutional layers and 2 pixels for the Maxpool layer is used. The output goes to another fully connected layer with 4096 neurons and is later fed into another fully connected layer with 1000 neurons. SoftMax is used to make the final decision to discern alphanumeric from the license plate. In Saudi license plates, there are Arabic and English alphanumeric portions. We trained our network with only English alphanumeric characters so, during validation when each batch passes through layers of CNN, the network found it hard to judge what was the Arabic portion. This situation has been shown in Fig 6. So there was a need to adopt the strategy to discard that Arabic portion. A clustering-based multi-language repudiate technique is used in which a strategy based on y-min and y-max is adopted. We discard the Arabic portion as it was near to y-min and keep the portion near to y-max as shown in Fig. 7. Now only the English alphanumeric text is passed through the network layers and therefore the system becomes robust eventually increasing the effectivity and accuracy of our proposed model as shown in Fig 8.

Fig 8: LP recognition results

4. RESULTS AND DISCUSSION

In this section, we conduct experiments to verify the effectiveness of our purposed methodology. All experiments were performed on the PyTorch framework. In the proposed methodology, different confidence thresholds are evaluated from 0.5 to 0.7. All vehicles in the validation set were detected as we considered Intersection over union (IoU) > 0.7, overlapping of annotated to the predicted bounding boxes Hence, we achieved recall of 99% with accuracy of 98% for detection of LP. For recognition of each alphanumeric digit and alphabets, augmentation and multi-language repudiate techniques proved helpful, increasing the overall recall/accuracy to 92.2%. Comparison of results are also shown in Fig 9, comparing morphological operation-based OCR and Multi language Repudiate based CNN Model.

Fig 9: OCR vs Machine Learning LP recognition results, Row 2 OCR, Row 3 Machine Learning

Which clearly shows the effectivity of our proposed CNN model over morphological based OCR algorithm for LP recognition. The overall accuracy of our model is shown in Fig 10. For comparison purposes, we use proprietary dataset images and augment them with different conditional techniques to evaluate our purposed methodology against commercially available OpenALPR and PlateRecognizer systems. The results are provided in Table 1. Our method performed well against available systems as both were unable to recognize when there were license numbers written in more than one language on the license plate hence our proposed model is not only robust to different variation in the

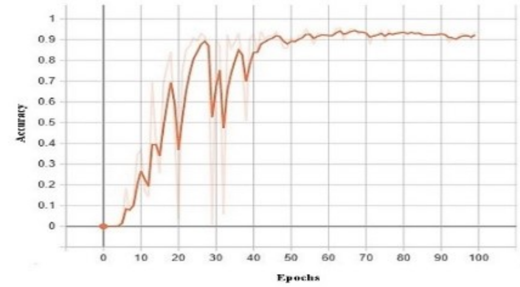

Fig 10: Multi Language Repudiate based CNN Accuracy

background but also best at repudiating multi-language torecognize LP, increasing the effectivity of ALPR System for different challenging situations which makes our proposed pipeline flexible and robust enough to perform well in real-world scenarios when used with Intelligent Transportation System (ITS), making cities smarter.

Model	OpenALPR	PlateRecognizer	**Ours**
UoJ Dataset	77%	67%	**92.2%**

Table 1: Recognition test-based results

5. CONCLUSION

In this paper, we proposed Multi-Language repudiate CNN model for LP recognition. The proposed methodology aims at presenting an efficient way to automatically recognize LP in real-time unconstrained scenarios. It also facilitates the ALPR system with the choice to discard multi-language when the license number is in more than one language on LP. This purposed methodology surely assists in gaining the desired feasibility by making the existing ALPR system plaint to diversifications of backgrounds, shooting up their effectivity when use with Intelligent Transportation System (ITS). The purposed methodology is evaluated on a custom dataset. Our purposed system achieved 92.2% accuracy which is better than commercially available systems of OpenALPR (77%) and PlateRecognizer (67%). Using LDR based dataset, a problem like uneven illumination due to overexposed and underexposed regions within the captured frame were encountered which happens when camera device sensors are unable to detect the high dynamic range generated by radiance map of natural scenes in the captured frame, resulting in loss of important information and eventually effecting the feasibility of ALPR system. However, this problem can be rectified in the future by using HDR images.

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