Number Plate Detection in An Image

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Abstract

Automatic Vehicle license plate detection and recognition is a key technique in most of traffic related applications and is an active research topic in the image processing domain. Different methods, techniques and algorithms have been developed for license plate detection and recognitions. Due to the varying characteristics of the license plate like numbering system, colors, style and sizes of license plate, When detection and recognition are two separate jobs, which also results in a huge number of factors, there is an issue with identification. So,further research is still needed in this area. We propose a unified convolutional neural network (CNN) and the F1 score as metrics in a deep learning project for picture categorization which can localize license plates and recognize the letters. We work on license plate recognition and segments characters in the license plate firstly, and then recognizes each segmented character using Optical Character Recognition(OCR)techniques. Extensive experiments show the effectiveness and the efficiency of our proposed approach.

1.INTRODUTION

Identification of licence plates is a key component of intelligent transportation systems. It can be used for a vast range of things, such as traffic control, self-driving cars, and parking toll booths. Identification of a licence plate in public is still challenging nowadays. Correctly reading licence plate characters in difficult-to-read conditions, such as occlusion, uneven lighting, rotation (large angle), vagueness, etc., is a difficulty. Investigation because it has some practical consequences. There are both segmented and unsegmented methods for identifying licence plates. Prior to using the Optical Character Recognition (OCR) methodology to recognise each character on the licence plate, each character on the plate must first be segmented. This approach, however, has a number of shortcomings. For instance, OCR recognition will not be accurate if the segmented characters are not complete[1].

Accuracy of this process can be impacted by factors like light intensity. Accuracy loss brought on by improperly segmented characters, this researchers lately selected the second method, which extracts the character properties. The approach presented in uses a Long Short Term Memory (LSTM) Network to recognise the whole sequence of plate features and transforms character recognition into a series annotation problem. This approach makes heavy use of computer capacity, doesn't necessitate character segmentation, and can precisely access the plate's contextual data[2].
Recognise complex scenarios. An open-source dataset with a variety of complex situations is recommended in their study. The planned technique on this dataset had a accuracy rate but could only identify one licence plate photo at a time. Developed a novel convolutional neural network (CNN) for the detection and correction of several distorted licence plates in a single image. Edge method on the CCPD dataset was employed to detect number plates; nevertheless, it has the drawback of being unable to read some types of plates. be instructed simultaneously over time. Which can precisely extract each character's local feature information and prevent character recognition issues brought on by incorrect character feature segmentation. Which doesn't need a separate module to handle number plate irregularities or segment characters for recognition[3].

1.1 Objective

The objective of image detection is to accurately and efficiently determine the presence and position of number plate in an image.

The creation of a number plate detection technique is the aim of this research. The system was instructed to use CNN to pull the license plate number from the picture.

1.2 Motivation

the project is to develop a highly accurate picture detection system for images of any resolution. It helps to select which areas of the image should be concentrated on in order to identify the number plate. In order to determine whether photographs contain a number plate, image detection technology use algorithms. The use of image detection technologies improves security and monitoring possibilities.

1.3 Existing Work

The inventors of the present method for detecting number plates in images used various machine learning and deep learning techniques, which resulted in lesser accuracy and a longer execution time. Even in the field of image tracking and detection, the majority of work appears to be focused on processing surveillance or identification, among other duties. Recent algorithms in this domain perform remarkably effectively and almost instantaneously with real-time, low-quality photos. However, when dealing with high-resolution, high-quality photos in movies or other industries that require such images, these algorithms become sluggish and less effective. A Multi-Task Cascaded Convolutional Networks technique is a deep learning-based image identification and alignment approach that detects and locates number plates in digital images or videos by using a cascading series of convolutional neural networks (CNNs).

1.4 Problem Statement

Automatic Vehicle license plate detection and recognition is a key technique in most of traffic related applications and is an active research topic in the image processing domain. Different methods, techniques and algorithms have been developed for license plate detection and recognitions. Due to the varying characteristics of the license plate like numbering system, colors, style and sizes of license plate, When detection and recognition are two separate jobs, which also results in a huge number of factors, there is an issue with identification. So,further research is still needed in this area.

Proposed Work

The proposed work is based on number plate quality recognition in an image, and it uses methods such as CNN to solve the problem of processing complicated data and obtain higher accuracy when compared to existing algorithms. The current algorithm only deals with high quality; the proposed approach includes high and low quality with 91% accuracy.

1.5 Advantages of proposed system

- Feature generation automation it is used by Deep Learning algorithms which can create new features from a small set of features present in the training dataset.
- It also works well with unstructured data, supports parallel and distributed algorithms.
- Deep Learning models can be expensive to train, but once they are trained, they can help businesses to reduce unnecessary expenditure and Scalability. [4].

1.6 Disadvantages of proposed system

- Deep Learning system needs to be trained on data by using huge amounts of data in order to get the best results.
- These recent advances in algorithm development are mostly the result of having algorithms run considerably faster than previously, which enables the usage of an increasing amount of data.
- Marketing has played an important role Neural network have been around for decades and have experienced peaks and valleys in popularity.

2.LITERATURE SURVEY

The following are the summarized review of literature of various recent studies done on Optimization of number plate detection from images.

In last few decades, quite a few learning based image quality methods have been proposed by researchers. Wang [5]: Deep convolutional neural networks (CNNs) in use today need an input image that is a fixed size, such as 224 224. With these benefits, SPP-net ought to enhance all CNN-based image classification techniques in general.

L. Xie [6]: The convolutional neural network (CNN)-based method for high-accuracy real-time car licence plate detection is presented in this paper. The proposed method surpasses other current state-of-the-art methods in terms of greater accuracy and cheaper computational cost, according to a number of trials conducted to support this claim.

W. Wang [7]: This paper's key contribution is the proposal of a multi-task convolutional neural network (MTLPR) for licence plate detection and identification (LPDR) with improved accuracy and reduced computational cost, as well as the introduction of a substantial data set of Chinese licence plate.

V. Pustokhina [8]: In the domains of computer vision and digital image processing, the process of detecting certain objects in an image is essential. Because of differences in viewpoint, shape, colour, different formats, and non-uniform illumination conditions at the moment of image acquisition, the Vehicle License Plate Recognition (VLPR) process is difficult.

Alam [9]: The method then separates the area of the number plate from the image range. A super resolution approach is then used to transform the low-resolution image into a high-resolution image after the number plate region has been extracted. Convolutional layer of CNN and super resolution technique are used to recreate the pixel quality of the input image.

S. -L. Chen [10]: Due to the inclusion relation, the vehicle can influence the detection of the licence plate with a single network. In this study, we present an end-to-end deep neural network for recognising the vehicle and the licence plate concurrently in a given image. Two independent branches with various convolutional layers are developed for the detection of the vehicle and the licence plate, respectively.

Tourani [11]: This study suggests a technique for real-time performance and significant accuracy in the detection of car licence plates and character recognition. The aforementioned system is made for Iranian vehicle licence plates, which have unique resolution and layout requirements, few numbers or characters, a wide range of background colours, and variable text sizes.

L. Zhang [12]: suggest a reliable framework for recognising licence plates in the wild. It is made up of an elaborately built image-to-sequence network for plate recognition and a customised CycleGAN model for creating licence plate images. However, the 2D attentional based licence plate recognizer using an Xception-based CNN encoder can accurately and robustly identify licence plates with various patterns in a variety of settings.

Raza [13]: In order to create intelligent settings, licence plate recognition (LPR) systems are essential components of intelligent transportation systems. Two crucial LPR stages—License plate character segmentation (LPCS) and License plate character recognition—are included in the proposed design (LPCR). Red-Green-Blue (RGB) channel-based colour maps are suggested as a method for a foreground polarity detection model that can successfully segment and identify LP characters at both the LPCS and LPCR stages.

O. Bulan [14]: Several applications for roadway imagery require automated licence plate recognition (ALPR). In this research, we present a revolutionary ALPR workflow with enhanced plate localisation, automation for failure identification, and segmentation- and annotation-free ALPR techniques.

Y. Y. Lee [15]: One of the applications that greatly profited from Convolutional Neural Network (CNN) processing, which has become the standard processing approach for complicated data, is Automatic License Plate Recognition (ALPR).

Q. Huang [16]: The majority of automatic licence plate recognition (ALPR) techniques now in use concentrate on a single type of licence plate (LP), with mixed or multiple LPs receiving less attention. This article suggests the use of ALPRNet, a single neural network, to identify and detect mixed-style LPs.

Mahmood [17]: In this study, we create an effective licence plate detection method using an intelligent combination of digital image processing methods and Faster R-CNN. Through the use of Faster R-CNN, the suggested algorithm first detects any vehicles in the input image. In the following stages, a powerful License Plate Localization Module analyses the discovered car (LPLM).

Alghyaline [18]: The objective of this study is to create a reliable ALPR for Jordanian LPs. In the suggested approach, CNNs with two stages are employed. These CNNs are based on the YOLO3 architecture.

C. Henry [19]: This study offers a deep ALPR solution that can be used by multinational LPs to address this problem. The suggested method consists of three basic steps: transnational LP layout detection, unified character recognition, and LP detection. You only look once (YOLO) networks form the foundation of the system in large part.

C. Liu [20]: propose a novel hybrid cascade structure in this study for quickly identifying small, hazy licence plates. We suggest two cascade detectors—the Cascaded Color Space Transformation of Pixel detector and the Cascaded Contrast-Color Haar-like detector—for the quick extraction of licence plate candidates.

M. S. Beratoğlu [21]: This study demonstrates for the first time that LP detection can be carried out without completely decompressing the encoded material. High Efficiency Video Coding (HEVC)-based compressed video sequences are used to implement the suggested technique. There are two ways offered for creating images from HEVC characteristics.

Q. Huang [22]: In light of the foregoing, this paper suggests a multi-style licence plate recognition method based on feature pyramid networks with instance segmentation. This method eliminates the steps of segmentation and optical character recognition found in conventional methods and converts licence plate recognition into object instance detection.

Han[23]: Present a novel method of multi-oriented and scale-invariant licence plate identification (MOSI-LPD) based on convolutional neural networks to address the aforementioned issues. Regardless of the scales of the licence plate, our MOSI-LPD firmly encloses the multi-oriented licence plates with bounding parallelograms.

M. Molina-Moreno [24]: In this study, we propose a scale-adaptive deformable part-based model that, based on a well-known boosting algorithm, automatically models scale during the training phase by choosing the most prominent features at each scale and noticeably decreases the test detection time by avoiding the evaluation at different scales.

W. Weihong [25]: Deep learning has enabled the licence plate recognition algorithm to extract deeper characteristics, considerably increasing the accuracy of detection and identification. As a result, the main effort discussed in this paper is the use of deep learning for licence plate recognition.

Nguyen [26]: This study develops a lightweight feature pyramid generating module based on a lightweight architecture and depth-wise convolutions to extract high-level features from input photos. An effective feature enhancement module is created to combine backbone features with features produced by the region proposal network in order to further improve the feature pyramid.

Ahmed [27]: The usage of automatic number plate recognition (ANPR) has become commonplace in a variety of industries, including tolling, parking management, traffic control, and intelligent transportation systems. In this research, we implement a case study for smart car towing management using Machine Learning (ML) models to investigate these issues.

Saeed [28]: The suggested system uses the YOLO (You Only Look Once) object detection model to locate the number plate region. The segmented image was used as an input for a LeNet Convolutional Neural Network (CNN) architecture for comparison and validation.

Liu [29]: Running vision-based apps on Internet of Things (IoT) devices has gotten increasingly difficult due to the blooming development of both computer vision and IoT technology. Automatic License Plate Recognition (ALPR) is one of the core services for smart-city applications like traffic control, autonomous driving, and safety monitoring in vision-based systems.

Tung [30]: This study adopted multitask learning in the licence plate detection stage, used the convolutional neural networks of single-stage detection, RetinaFace, and MobileNet, as approaches to licence plate location.

S.no	**Author name**	CNN	YOLO	ILPRNET	RPN	FRCNN/ DCNN	SVM	K-Means	CycleGAN	KNN
1	Kim	YES								
2	Hui	YES	YES							
3	Zou		YES	YES						
4	N. Duan	YES								
5	K. He	YES								
6	L. Xie	YES	YES							
7	W. Wang	YES								
8	V. Pustokhina	YES						YES		
9	Alam	YES								
10	S. -L. Chen	YES	YES			YES				
11	A. Tourani	YES	YES							
12	L. Zhang								YES	
13	Raza	YES		YES						
14	O. Bulan	YES								
15	Y. Y. Lee	YES	YES							
16	Q. Huang	YES				YES				
17	Mahmood									
18	Alghyaline	YES	YES							
19	C. Henry		YES							
20	C. Liu and F. Chang	YES								
21	M. S. Beratoğlu		YES							
22	Q. Huang	YES								
23	Han	YES								
24	M. Molina-Moreno	2018								
25	W. Weihong	YES								
26	Nguyen	YES								
27	Ahmed									YES
28	Saeed	YES	YES							

29	Liu										
30	Tung	YES									

2.1.Summary: Table for Authors and Algorithm used

3.DESIGN METHODOLOGY

3.1 System Architecture

The procedure CNN is used in the suggested system's architecture. The algorithm detects the number plate and identifies the number plate features. The scale, translation, and rotation between the original and new places are then estimated. The bounding box is transformed using this transformation.

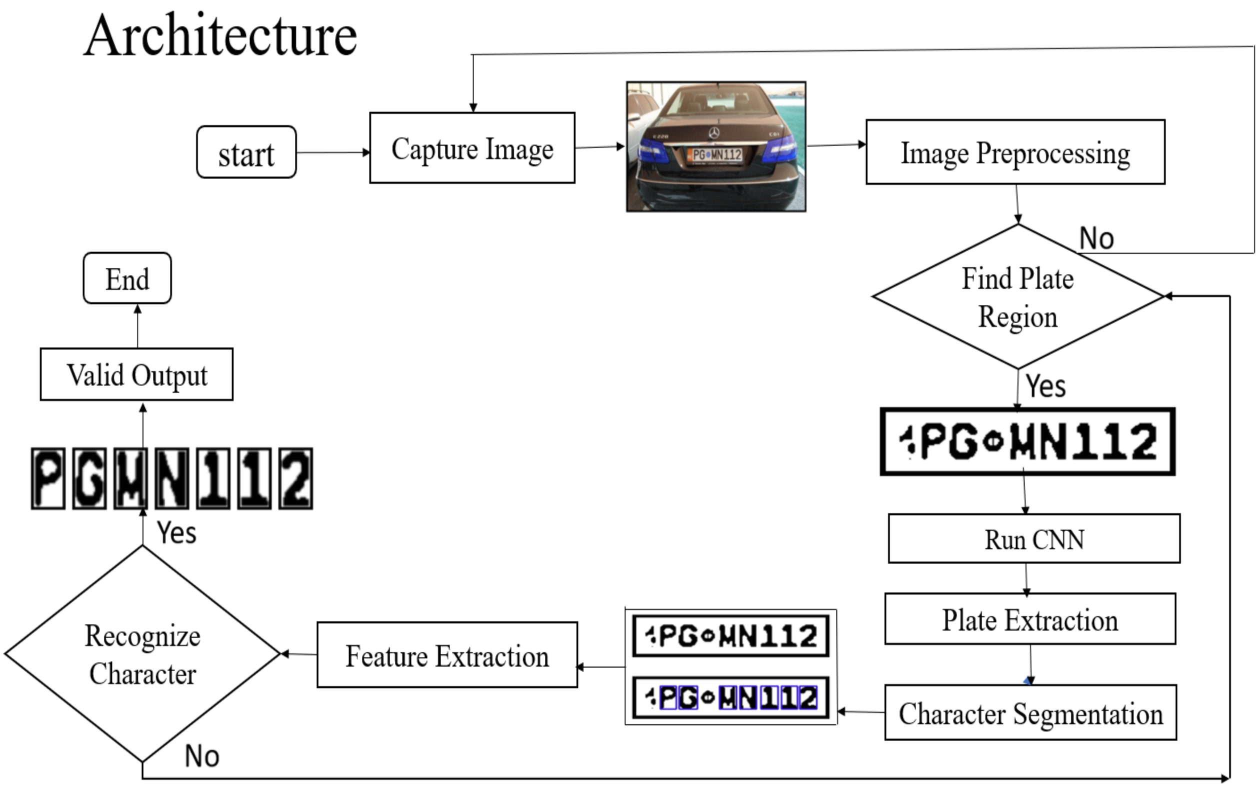

Figure 3.1 System Architecture

The above figure 3.1 displays the suggested system's architecture. The user will provide an image as input, which will be separated into images. Preprocessing is performed on the pictures, and the next step is to increase the refresh rate. The algorithms perform based on the refresh rate. [30]

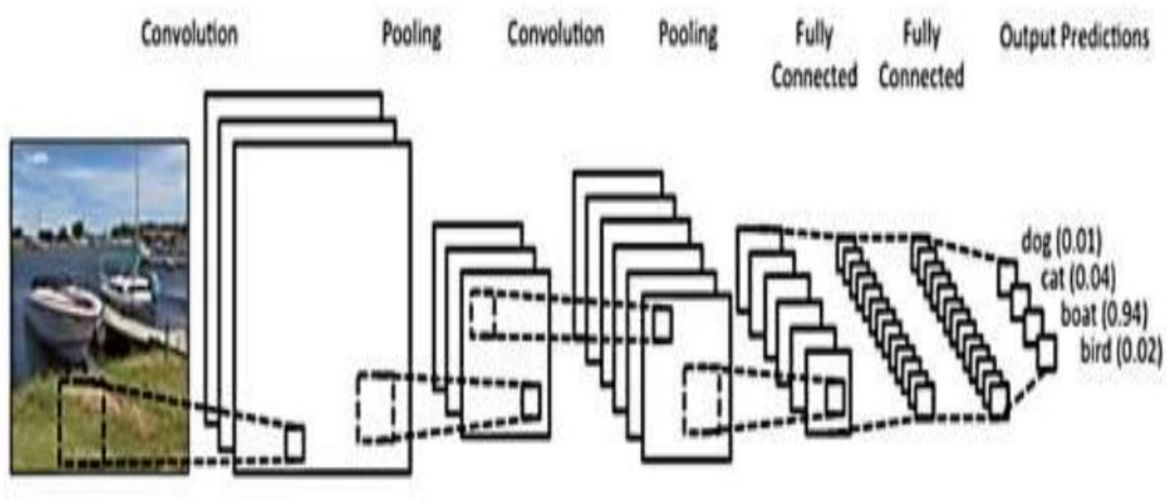

Figure 3.2 Architecture of CNN

3.2 Convolutional Neural Network: One of the most popular deep neural networks is Convolutional Neural Networks (also known as CNN or Conv-Net) in deep learning, especially when it comes to Computer Vision applications.

1.Convolutional Layer:

- The core building block of CNN is the convolutional layer.
- It applies a set of learnable filters (also known as kernels or feature detectors) to input data, typically an image.
- The filters slide over the input data, computing dot products between the filter weights and the local receptive fields, capturing spatial patterns and features.
- Each filter generates a feature map, highlighting different aspects of the input data.

2.Pooling Layer:

- After one or more convolutional layers, pooling layers are often added to reduce the spatial dimensions of the data.
- Pooling performs down sampling by summarizing information within local neighborhoods of the feature maps.
- Common pooling operations include max pooling (selecting the maximum value within a neighborhood) or average pooling (taking the average).
- Pooling helps to reduce the computational complexity and extract important features, making the network more robust to small spatial translations or distortions.

3.Activation Function:

- An activation function is applied to the output of each neuron in a CNN layer.
- Common activation functions include ReLU (Rectified Linear Unit), which introduces non-linearity and helps the network learn complex relationships.
- Activation functions introduce non-linear transformations, allowing CNNs to model complex mappings between inputs and outputs.

4.Fully Connected Layer:

- Following one or more convolutional and pooling layers, CNNs often have one or more fully connected layers.
- Fully connected layers connect every neuron in the previous layer to every neuron in the subsequent layer.
- These layers serve as the “classifiers” or “decision makers” of the network, combining information from different parts of the input to make predictions or classifications.

5. Training and Backpropagation:

- CNNs are trained using labeled data through a process called backpropagation.
- Backpropagation involves iteratively adjusting the weights of the network based on the difference between predicted outputs and true labels.
- Optimizers, such as stochastic gradient descent (SGD) or Adam, are commonly used to update the weights in the network.
- The learning process aims to minimize a loss function, such as cross-entropy, that quantifies the discrepancy between predicted and true labels. By stacking multiple convolutional, pooling, and fully connected layers, CNNs can automatically learn hierarchical representations of data, capturing features at different scales and levels of abstraction. This capability enables CNNs to excel in various computer vision tasks, including image classification, object detection, image segmentation, and more [28].

CONCLUSION

There are number of reasons that can affect the quality of a number plate image. These reasons can range from presence of different image sensors, compression algorithms, video or image acquisition conditions, time of acquisition etc. For these varied reasons, automatic number plate image quality assessment is a very challenging subject. In recent years a number of learning based FIQA methods have been proposed which provides good prediction of number plate recognition performance based on the number plate image quality score. This paper deals with three parameters of performance runtime efficiency, accuracy of the detected number plate, and occlusion resolution in between frames. Our model achieves optimal performance by trading-off between speed and accuracy. This model can be improved upon by choosing a faster and more accurate base face detection algorithm, since its performance is still dependent on the initial number plate detecting algorithm chosen for the model. In future scope Because of the high performance, face detection method with video segmentation can be widely applied to track faces in massive video data.

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