License plate recognition using Machine Learning

IMMEDIATE

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Car owners altering license plates using different typefaces and designs violate the law that strictly forbids such behaviour. Traffic police officers claim that changing the license plates makes it impossible to read the registration numbers due to an increase in fatal street collisions and car thefts. They worry that it may be difficult to track down vehicles used in hit-and-run incidents. It is challenging to impose further limitations on any algorithm used to identify and recognise license plates in a developing nation like Bangladesh. This work has the primary objective of designing a reliable detection and recognition system for transitional, standard car license plates, which are frequently seen in developing countries. Increase the effectiveness of reading license plates drawn or printed in various styles and typefaces employing cutting-edge technology, including machine learning (ML) models. For this study, You Only Look Once (YOLOv3) is used to utilising the most recent version of the object detection method. The raw image is pre-processed to increase its quality and then divided into appropriate-sized grid cells to determine where the license plate should be placed. After that, the data is post-processed, and the accuracy of the proposed model is evaluted using industry-recognised standards. A sizeable image dataset was used to be tested using this proposed methodology. The presented system is expected to be essential for vehicle monitoring, parking fee collection, lowering traffic accidents, and identifying unregistered vehicles. The results demonstrate that the suggested method achieves 97.1% mAP, 95.3% precision and 96.8% in plate detection.

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1. INTRODUCTION

License plate identification has gained much attention due to the increase of automobiles and the installation of cameras that monitor traffic. Recognition of license plates aids in identifying vehicles, tracking, and activity analysis for surveillance and security applications. Vehicle monitoring has become a research challenge as the need for traffic control and increasing safe vehicle tracing systems. It is often humans are tasked with monitoring works, which is monotonous, inefficient and prone to errors and mishaps. As opposed to that, a computerised system can quickly and accurately recognise license plates from still images. Manually inspecting every vehicle on the road is challenging. Global issues with owner identification and traffic control are being explored to develop intelligent transport systems (ITS). These technologies will offer the necessary cutting-edge services for managing traffic and modes of transportation. With intelligent systems, ITS will assure efficient and safer transport network . Through cameras placed at various locations along roads, the license plate recognition system recognises the nameplate information of the vehicles. Additionally, it is crucial to ITS that it has several practical implementations, including vehicle monitoring, parking fee collection, over-speed vehicle detection, reducing traffic accidents, and identifying and tracking unauthorised or counterfeit vehicles. However, several issues make automatic license plate recognition (ALPR) systems less effective. Such as, Occlusions, rotations, and complex traffic jam scenarios that occur in real-world settings, as shown in Fig 1, reduce the effectiveness of most current techniques.

Similar to how many existing methods are accurate and effective for indoor stationery. Convolutional neural networks and automatic number plate recognition have been studied to detect moving car speeds and assess red-light running on traffic routes. Using various license plate kinds, hanging the plates at various heights, varying license plate sizes and colours, and using non-standard fonts and templates are further issues hampering the development of such systems in emerging nations. In Fig. 2, an example of such an issue is displayed.

Single-stage deep-learning-based ALPR systems give the system analysis that will drive the entire mechanism toward recognition studies with far greater stability. Good precision should also be considered for the associated plate number,however, doing so frequently comes at a high processing cost that is un-

Fig. 1. The Dhaka city roads were severely gridlocked amid a huge rush of traffic on Thursday.(The photo was taken from Farmgate intersection. photo: Observer)

Fig. 2. illegal license plate. Image taken from https://www.thedailystar.net/news-detail-125506

sustainable for real-time operations[2]. Contrarily, because to their lower processing complexity, multi-stage approaches with modest accuracy can easily be expanded for real-time functions. Consequently, for non-conventional license plates standard in developing nations, this study provides a multi-stage nameplate recognition method. The following contributions are made by this study, in brief-

· This paper details a method for detecting and identifying license plates based on deep learning. The initial stage involves locating the plate's location to detect it and then processing the detected license plate area to determine the plate's contents. · A 53-layer deep CNN architecture is used for plate identification, and it is built on the most up-to-date object detection algorithm, YOLOv3 (or "You Only Look Once, Version 3"), which emerged on the algorithm of real-time detection of the object. It is employed to locate particular items in photos, live feeds, or movies. CNN structure is used to recognize registration plates with high precision and consistent output.

2. LITERATURE REVIEW

Over the past 20 years, the widespread use of personal vehicles has presented several issues, including effective traffic control, tracking vehicles that break traffic laws, locating cars that have been stolen, and security surveillance. The detection and identification of the vehicle license plates are necessary for these duties. As a result, there is a sizable body of research in the literature that concentrates on identification of license plates.. Different approaches are described following how license plate identification problems differ depending on the characters used in different accuracy of 76% are all attained. The authors used the inception method to address the issue of license plate detection in [7]. The suggested method seeks to extract license plates from poor, dim photos. The focus is on plate identification issues in languages. A smearing algorithm can be used to recognise license plates in both single and double lines. Character segmentation accuracy of 96%, plate localisation accuracy of 97.4%, and character recognition access such as character recognition, segmentation, and blob extraction. An accuracy of 98.40% in recognition can be offered by the method. The United Kingdom's number plate recognition in [10] uses automatic number plate recognition for practical applications. The system incorporates a lot of real-world elements, such as screw fastening, typeface variety, spacing, colour, and various number plate symbolism presents a two-stage method for recognising license plates, with the plate localisation being handled using fuzzy disciplines and the recognition being handled by neural networks [11]. Images collected from diverse scenes assess how well the suggested technique works. The system's accuracy for locating license plates is 97.9%, and its success rate for identifying plates is 95.6%. In [3],Red, Green, and Blue channels are used by the authors to divide the license plate identification issue. Each channel's image serves as the input for CNN, this learns the topological characteristics using the data. SVM then uses the findings to create the target probability label values. Similar to this, [4] employs CNN-based techniques for a multi-directional license plate identification system that makes use of the multi-directional you only look once (MD-YOLO) framework. The suggested framework has the highest detection precision for multi-directional challenges. Every object's centre coordinate, together with its width and height, is predicted by MD-YOLO. The authors train the informative system in [5] using a deep learning method divided into three sections: role recognition, cutting, and detection. Numerous pre-treatment processes have been taken to detect license plates, and it has been decided to use the CNN model application.Then, the shapes (A-Z) and numbers (0-9) are explained.. [6] discusses a unique form of feed-forward multilayer perceptron. The suggested supervised model has the ability to extract features automatically for license recognition. The technology being used primarily aims to improve character recognition performance by utilising a customised CNN. In [8], the authors offer a method for recognising license plates under Australian conditions. It deals with variations in the appearance of several plats brought on by the usage of various designs and colours from various states. In addition, the use of unconventional materials and the plates inserted inside the coverings present additional difficulties. The suggested method uses artificial neural networks and image processing to identify distinct plates with a 0.95 accuracy. In [9], a license plate identification system based on scale-invariant feature transform (SIFT) characteristics is given. The recognition of license plates was the primary goal of this research. The method is employed to recognise license plates with Chinese characters. Variations in illumination, partial occlusion, and poor character are considered. The method offers 100% character segmentation accuracy and 96% candidate filtration accuracy. In [12], the authors suggest using sensors to manage a barrier that includes a system for recognising a vehicle's license plate based on an image. The suggested method recognises license plates under challenging conditions such as changing license plate backgrounds, using multiple typefaces, and having deformed plates. Characters are detected for this purpose using a typical optical character recognition pipeline. For license plate extraction, character segmentation, and character identification, the method obtains an accuracy of 98%, 96%, and 93%, respectively.

3. PROPOSED METHODOLOGY

YOLOv3 (YOU ONLY LOOK ONCE, Version 3): This YOLO machine learning algorithm version is more accurate than the previous ones. It has significant differences in speed, accuracy and architecture compared to the previous versions. Since 1*1 convolutions are used in the YOLO algorithm's prediction, the prediction map's size exactly matches that of the feature map that came before it, hence the title "you only look once."A Convlutional Neural Network also called CNN can identify patterns. Classification is done to identify patterns in images. This classification is done under multiple classifiers. Despite being considerably fast the accuracy does not lessen. The algorithms dissect the images into grids. Each grid cell predicts the presence of a specific number of boundary boxes around items that perform well in the aforementioned predetermined classes. Only one object is detected by each boundary box, which has a corresponding confidence score indicating how accurate it expects that prediction to be. R-CNN (Region-based Convolutional Neural Networks), Fast R-CNN (an R-CNN upgrade), and Mask R-CNN are different comparable algorithms that can accomplish the same goal. However, YOLO is taught to perform classification and bounding box regression simultaneously, unlike R-CNN and Fast R-CNN systems.

Fig. 3. data processing

The research approach flowchart is shown in Figure 3 for the current study, and each step is detailed in depth in the following sections. Using big data and extensive science surveys to provide the necessary designs, including data science, is recommended by methodology. These are carried out with the aid of comparative analyses of the already developed mechanisms in this area of data mining and its categorisation according to localisation and segmentation[15,16].

A. Data Gathering

Images of local Bangladeshi automobiles are gathered from various sources at the beginning of the technique. Like in many other nations, license plate sellers do not adhere to a set standard for license plate designs, and some additional customs include engraving names, images, and phrases next to or around the license plate number[16]. Labs and license plates are annotated using Roboflow after data collection. This study uses a dataset[18] where there remain pictures of automobiles with license plates.

B. Vehicle License plate dataset

The dataset[18] consists of 1845 images. There are 1845 random photographs of Bangladeshi automobiles in the image folder, none of which are organised in any particular way. The coordinates (x-min, y-min, x-max, and y-max) in the annotation folder show where the license plate from the vehicle image is located.

C. Pre Processing:

Pre-processing is used to enhance critical picture functionalities or suppress unneeded distortion to improve image data quality for further processing. Because of this, deformed pixels can frequently revert to the average of their neighbouring pixels. To feed the neural networks, the picture pixel values are transformed into a size of 416 by 416. This process is used to prevent neural network density that is unneeded. The following actions are taken for picture pre-processing.

D. Read images

In this stage, we read the image first. Images come in various formats, including JPG, PNG, and MPEG.

E. Resize image

Using the OpenCV library, the photos are shrunk in size in this stage. Size reduction aids in lowering the computational complexity of neural networks and the feature vector.

F. Image normalization

The goal of picture normalization is to prepare the data by distributing the pixel values across all images according to a common statistical distribution. The picture array is divided by 255 for this reason in order to normalize the image. Intensity normalization is another name for normalizing an image's pixel values [17].

G. Identifying plate location

License plate localisation are crucial component of the license plate recognition system. Algorithm proposals are made in order to achieve localisation[18]. The (bbx, bby) coordinate indicates the object's centre in relation to the grid cell location, and this (bbw, bbw) coordinate displays the bounding box's width and height in relation to the image dimension [7].

4. RESULT

The bounding box highlights the license plate. The license plate was detected with a confidence level of 0.482. However there are quite a few limitations to this model. In case of multiple vehicles and distortion of images the model fails to recognize the number plate like in fig 6.The image contains three or more vehicles and out the three, the license plates of all three are visible, however the model fails to detect the license plate of the two in the back.

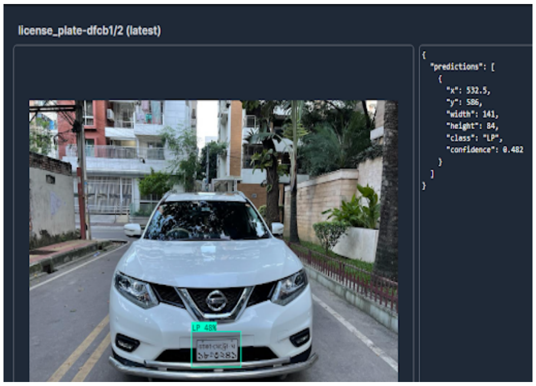

Fig. 4. Car plate detection model demonstration. picture taken from https://bhalogari.com/featured-used-car/car-details/Nissan-X-Trail?car$_i d = 2110$

Fig. 5. Limitations of the model. picture taken from https://bcmgbd.com/cars-hire-service-for-vip-in-dhaka-bangladesh/

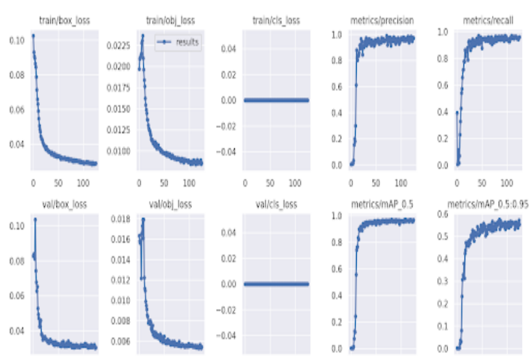

Fig. 6. Training and validation loss of YOLOv3

A. Training and testing

The dataset[18] is divided into three categories. Out of 1845, 1472 images were picked in order to train the model. 183 went into validation and the rest of 190 went into testing. The lion share of the images are put in the training category. The pre-processing step includes resizing and feature extraction. No further augmentation was put in before the training process. The trained model was then executed over the testing and validation dataset. The following graphs showcase the training loss, precision, recall,mAP of the YOLOv3 algorithm

5. CONCLUSION

Vehicle tracking has emerged as a crucial study field for effective traffic management, monitoring, and recovering stolen automobiles as the number of vehicles has increased. In developing nations like Bangladesh, recognizing license plates is very difficult because of the variance in background and plate size, as well as non-standard characters. This work uses a deep-learning approach to increase the effectiveness of license plate recognition to get around these problems. A significant picture data collection of several types of license plates seen in Bangladesh is used to evaluate the proposed methodology. The gathered photographs were taken in a variety of lighting and contrast situations, at differing distances from the camera, and with varying angles of rotation. They were then confirmed to produce a high identification rate. Law enforcement authorities and commercial businesses can employ the strategy to increase national security. Future work may involve character recognition systems in license plates in both Bengali and English language and numerical characters. Because it is also a challenge to read letters with different types of font colors and font styles in license plates. Furthermore, some works may involve improving the resilience of the license plate identification system in various weather circumstances as well as training and validating the current algorithm utilizing the hybrid classifier method.

REFERENCES

1. M. S. Sarfraz, A. Shahzad, M. A. Elahi, M. Fraz, I. Zafar, and E. A. Edirisinghe, "Real-time automatic license plate recognition for cctv forensic applications," J. real-time image processing **8**, 285–295 (2013).
2. A. Badr, M. M. Abdelwahab, A. M. Thabet, and A. M. Abdelsadek, "Automatic number plate recognition system," Annals Univ. Craiova-Mathematics Comput. Sci. Ser. **38**, 62–71 (2011).
3. D. Bhardwaj and H. Kaur, "Comparison of ml algorithms for identification of automated number plate recognition," in *Proceedings of 3rd International Conference on Reliability, Infocom Technologies and Optimization,* (IEEE, 2014), pp. 1–6.
4. C.-T. Hsieh, Y.-S. Juan, and K.-M. Hung, "Multiple license plate detection for complex background," in *19th International Conference on Advanced Information Networking and Applications (AINA'05) Volume 1 (AINA papers),* vol. 2 (IEEE, 2005), pp. 389–392.
5. S. A. Radzi and M. Khalil-Hani, "Character recognition of license plate number using convolutional neural network," in *International Visual Informatics Conference,* (Springer, 2011), pp. 45–55.
6. M. Abdullah, M. A. H. Bakhtan, and S. A. Mokhtar, "Number plate recognition of malaysia vehicles using smearing algorithm," Sci. Int.(Lahore) **29**, 823–827 (2017).
7. L. G. Hamey and C. Priest, "Automatic number plate recognition for australian conditions," in *Digital Image Computing: Techniques and Applications (DICTA'05),* (IEEE, 2005), pp. 14–14.
8. Y. Wang, X. Ban, J. Chen, B. Hu, and X. Yang, "License plate recognition based on sift feature," Optik **126**, 2895–2901 (2015).
9. M. Rhead, R. Gurney, S. Ramalingam, and N. Cohen, "Accuracy of automatic number plate recognition (anpr) and real world uk number plate problems," in *2012 IEEE international carnahan conference on security technology (ICCST),* (IEEE, 2012), pp. 286–291.
10. S.-L. Chang, L.-S. Chen, Y.-C. Chung, and S.-W. Chen, "Automatic license plate recognition," IEEE transactions on intelligent transportation systems **5**, 42–53 (2004).
11. F. Ullah, H. Anwar, I. Shahzadi, A. Ur Rehman, S. Mehmood, S. Niaz, K. Mahmood Awan, A. Khan, and D. Kwak, "Barrier access control using sensors platform and vehicle license plate characters recognition," Sensors **19**, 3015 (2019).
12. A. Menon and B. Omman, "Detection and recognition of multiple license plate from still images," in *2018 International Conference on*

Circuits and Systems in Digital Enterprise Technology (ICCSDET), (IEEE, 2018), pp. 1–5.

13. Y. Chen, H. Chen, A. Gorkhali, Y. Lu, Y. Ma, and L. Li, "Big data analytics and big data science: a survey," J. Manag. Anal. **3**, 1–42 (2016).
14. L. Zheng, T. Sayed, and F. Mannering, "Modeling traffic conflicts for use in road safety analysis: A review of analytic methods and future directions," Anal. methods accident research **29**, 100142 (2021).
15. A. Puranic, K. Deepak, and V. Umadevi, "Vehicle number plate recognition system: a literature review and implementation using template matching," Int. J. Comput. Appl. **134**, 12–16 (2016).
16. D. M. Babu, K. Manvitha, M. Narendra, A. Swathi, and K. P. Varma, "Vehicle tracking using number plate recognition system," Int. J. Comput. Sci. Inf. Technol. **6**, 1473–1476 (2015).
17. J.-M. Guo and Y.-F. Liu, "License plate localization and character segmentation with feedback self-learning and hybrid binarization techniques," IEEE transactions on vehicular technology **57**, 1417–1424 (2008).
18. Research, "Licenseplate dataset," https://universe.roboflow.com/research-nodmu/license_plate-dfcb1 (2022). Visited on 2022-08-27.

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