Automated Recognition of Uzbekistan Automobile License Plates: A Robust ANPR System

Asrorbek Eraliev
asrorbek.eraliev@polito.uz
Jaloliddin Yusupov
jaloliddin.yusupov@polito.uz
Turin Polytechnic University in Tashkent

Abstract: In today's modern world, Automatic Number Plate Recognition (ANPR) systems play a pivotal role in various applications, including law enforcement, traffic management, and security. This paper presents a comprehensive ANPR system specifically tailored for recognizing Uzbekistan automobile plate numbers. The developed model integrates advanced image processing and Optical Character Recognition (OCR) techniques to achieve accurate and efficient license plate recognition specifically the Uzbekistan automobile plate numbers. The system's versatility is demonstrated through successful testing on static images and live video feeds, showcasing its potential for widespread deployment.

Keywords: ANPR, Uzbekistan, image processing

I. Introduction

In today's era of technological advancements, the integration of Automated Number Plate Recognition (ANPR) systems has become imperative for enhancing security, law enforcement, and traffic management. Recognizing the distinctiveness of license plates is crucial for the effective operation of these systems. This paper marks a pioneering effort as the first to address the specific nuances presented by Uzbekistan license plates, focusing on their unique sequence and appearance. So far, any research has not been conducted on recognition of new Uzbekistan automobile plate numbers. This paper bridges the gap by introducing an ANPR system finely tuned to the specific sequence and appearance of Uzbekistan license plates, marking a significant contribution as the first paper on this topic.

A. *Literature Review*

Various approaches have been proposed to address the challenges associated with automatic license plate recognition (ALPR), focusing on aspects such as character recognition, vehicle image capture, license plate detection, and plate segmentation [1-3]. Automatic license plate detection (ALPD) is a method employed to autonomously extract the license plate area of a vehicle from an image or video frame, eliminating the need for human intervention [4]. Traditionally, machine learning techniques have been integral to automatic license plate recognition systems, focusing on capturing specific morphological attributes like color and text. These systems exhibit a robust capability to handle complex backgrounds and image noise [5]. An innovation in image processing, Automatic Number Plate Recognition (ANPR) employs optical character recognition on images to capture vehicle registration plates and convert them into machine-readable formats. This process facilitates subsequent indexing into an appropriate database [6-8]. The ANPR system comprises three key components: vehicle number plate extraction, character segmentation, and Optical Character Recognition (OCR). The initial stage involves license plate extraction, where the system detects the presence of a vehicle license plate.

In the past decade, numerous endeavors have been undertaken to address the challenge of identifying potential License Plate (LP) areas from images or videos. A notable proposal by [9] suggested the installation of high-definition video cameras at intersections to continuously detect and capture vehicle images. Consequently, Digital Video Recorders (DVRs) have been seamlessly integrated with Closed Circuit Television (CCTV) systems to manage and store extensive datasets [10]. To enhance image acquisition and eliminate extraneous features, sensors and other hardware peripherals are employed. This has not only improved the accuracy of License Plate Recognition (LPR) systems but also contributed to advancements in surveillance and forensic applications.

In the realm of research, Sasi et al. introduced a novel approach to LP detection by utilizing plate localization for edge detection. Their study, titled "Automatic Car Number Plate Recognition," incorporated the Modified Ant Colony Optimization Algorithm and the Kohonen neural network for character location and classification [11].

Similarly, [2] focused on Image Extraction from Number Plates, employing an area extraction technique and morphological image processing through deep learning. This involved using a pre-trained Convolution Neural Network (CNN), specifically the “Alex-Net” algorithm, as a feature extractor, with Support Vector Machines (SVM) serving as a classifier. The algorithm, implemented in C++, demonstrated effectiveness in morphological image processing.

Addressing motorcycle safety concerns, Jamtsho et al. proposed a convolutional neural network for the automatic detection of License Plates (LP) from video streams, emphasizing the need for the safety of non-helmeted motorcyclists [12].

Satsangi et al. conducted a comparative study titled “License Plate Recognition: A Comparative Study on Thresholding, OCR, and Machine Learning Approaches.” Their research explored license plate recognition using the Viola Jones algorithm, focusing on character classification and recognition. The study evaluated the performance of the Viola Jones algorithm against thresholding and OCR technologies, with Viola Jones demonstrating the highest accuracy of 80 percent [13].

Omar et al. analyzed various image processing techniques using a cascaded deep learning approach, revealing that Automatic License Plate Recognition systems benefit from preprocessing techniques with filtering and contrast enhancement capabilities [14].

Gao et al. adopted a quantitative approach to assess privacy disclosure risks in an LPR dataset, highlighting the potential re-identification of anonymous individuals. Their study concluded that even with temporal granularity set to half a day, five spatiotemporal records were sufficient to uniquely identify about 90% of individuals [15].

Selmi et al. proposed a Deep Learning System for Automatic License Plate Detection and Recognition. Their approach involved preprocessing procedures to identify license plates and non-license plates, utilizing two CNN models for detection, classification, and recognition. Character segmentation employed the canny edge detection approach, and character recognition was built on a Tensor Flow framework using a second CNN model with 37 classes [16].

Shivakumara et al. introduced keyword spotting in videos, natural scene images, and license plate images, facilitating accurate information retrieval from large and diverse databases [17].

Wang et al. developed a detection and tracking strategy for license plate detection in videos. Their study integrated cascade detectors and the TLD algorithm to detect license plates in video sequences. The cascade detectors were applied for both detecting newly appearing license plates and improving TLD's long-term tracking [18].

II. Methodology

In this study, our focus on recognition of automobile number plates automatically based on the following characteristics:

- Uzbekistan plate numbers
- Rectangle plates
- Single plate in which one line of characters
- Arrangement of letters and numbers

The work intended on detect and recognition specifically on only Uzbekistan automobile plate numbers. Fig 1 shows the Uzbekistan automobile plate number format.

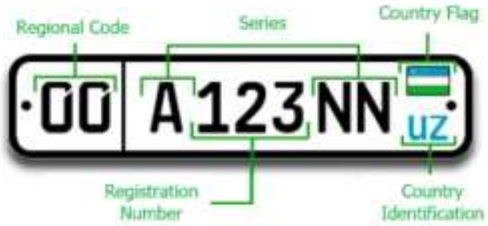

Fig. 1. Format of Uzbekistan automobile plates

The development of our ANPR model involves a systematic process encompassing the following key stages.

A. Image Preprocessing

The initial phase of our ANPR system involves a meticulous approach to image preprocessing, aimed at enhancing the quality of the input image and facilitating subsequent recognition processes. The series of operations performed during this stage are crucial in ensuring robust performance in varying environmental conditions.

The image undergoes a transformation into grayscale, a foundational step that simplifies subsequent processing. Grayscale conversion reduces the complexity of the image by eliminating color information, focusing the system’s attention on essential structural features. To mitigate noise and enhance the detection of edges, a Gaussian Blur is applied to the grayscale image. This smoothing operation helps in reducing the impact of irregularities and variations in pixel intensity, creating a more uniform image that aids in precise edge detection. Following Gaussian Blur, the Canny edge detection algorithm is employed to identify significant edges within the image (Fig2). This sophisticated technique excels in isolating edges based on intensity gradients, providing a clear representation of object boundaries. The resulting edge-detected image serves as a crucial foundation for subsequent contour detection.

a) b) c)

Fig. 2. a) Grayscale conversion b) Applied Gaussian Blur c) Canny Edge Detection output

The combination of grayscale conversion, Gaussian Blur, and Canny edge detection collectively prepares the image for the subsequent stages of license plate localization and character recognition. This preprocessing ensures that the ANPR system operates with heightened accuracy and reliability, even in challenging visual conditions.

B. License Plate Localization

The pivotal stage of our ANPR system lies in the accurate localization of the license plate within the input image. This process involves a meticulous analysis of contours detected in the preprocessed image. Contours, representing potential license plate candidates, are identified through the existing algorithm. During the iterative contour analysis, the system evaluates the aspect ratio of each candidate contour, employing predefined criteria to ascertain whether it aligns with the expected proportions of a license plate. This stringent validation helps filter out false positives, ensuring that only genuine license plate regions are considered for further processing.

One notable characteristic specific to Uzbekistan license plates is the presence of a distinct black border surrounding the alphanumeric characters. Leveraging this knowledge, the system intelligently crops the region enclosed by the identified contour, encapsulating the license plate within the surrounding black border. This strategic cropping is a crucial step, enhancing the subsequent OCR process's accuracy by isolating the license plate region from potential distractions in the background.

Fig. 3. License Plate Localization

This robust localization methodology not only ensures the precision of subsequent processing steps but also contributes to the overall efficiency and accuracy of our ANPR system. The incorporation of Uzbekistan-specific characteristics in this stage sets our model apart, demonstrating its adaptability to the unique visual attributes of license plates in the targeted context (Fig 3).

C. Text Extraction, Character Correction and Final Verification Algorithm

Following successful license plate localization, the next critical step in our ANPR system involves Optical Character Recognition (OCR) and the extraction of relevant text from the identified license plate region. This phase plays a pivotal role in converting the visual information captured from the license plate into a machine-readable format for subsequent processing.

The OCR process begins with the conversion of the localized license plate region to grayscale, facilitating enhanced character recognition. This grayscale transformation aims to standardize the image's color representation, reducing complexity and ensuring consistent OCR performance across various lighting conditions. The system employs state-of-the-art OCR algorithms to interpret the potential characters present on the license plate. Leveraging advanced pattern recognition and machine learning techniques, our model excels in accurately deciphering characters amidst challenges such as variations in font styles, sizes, and potential distortions due to the image acquisition process.

Since the standard length of the main text on Uzbekistan automobiles is eight characters, the system validates the extracted text's length to conform to this expected format. This length validation step serves as an initial filter to ensure the reliability of the extracted information. In scenarios where OCR may introduce errors or misinterpretations, particularly in the case of the regional code at the beginning of the text, a correction mechanism is implemented. This correction algorithm evaluates and rectifies potential mistakes in the extracted text, enhancing the overall accuracy of the recognition process. Furthermore, a distinct challenge arises from the presence of a vertical black line between the regional code and the registration numbers. In some instances, this line might be incorrectly recognized as the character '1' or 'I'. To address this issue, a specialized algorithm is developed to ascertain the correct identification of this line, further refining the accuracy of the OCR results. After these correction steps, a length correction algorithm is applied to the extracted image, aligning the characters precisely to mitigate potential errors introduced during the OCR process. This step ensures that the subsequent character recognition and verification steps are performed on accurately positioned characters. The algorithm meticulously examines each character extracted from the license plate region and corrects potential errors based on the relative positions of neighboring characters. For instance, the algorithm tackles prevalent confusions like '0' being recognized as 'O' or 'G', 'Z' being mistaken for '2' or '7', and 'O' being identified as '0'. Through a dynamic correction mechanism, the algorithm intelligently analyzes the contextual arrangement of characters and applies corrections accordingly. By considering the spatial relationships between characters, the system significantly mitigates the impact of misreadings, contributing to the overall precision of the license plate recognition process.

The final verification algorithm represents the final layer of scrutiny in our ANPR system, ensuring the accuracy of the recognized text. This algorithm is designed to evaluate each character individually, verifying whether it aligns with the expected format of a license plate in Uzbekistan. The algorithm specifically addresses situations where a letter is inaccurately identified as a digit or vice versa. The verification process involves cross-referencing each character against a set of predefined rules that adhere to the structure of Uzbekistan license plates. Any deviation from the expected arrangement prompts corrective measures, refining the accuracy of the final recognition. By meticulously assessing each character in isolation, the verification algorithm adds an additional layer of reliability to the overall license plate recognition process.

D. *Live Video Recognition*

Building upon the success of static image recognition, our ANPR system seamlessly transitions to real-time scenarios through live video recognition. This capability holds immense significance in dynamic environments, such as urban traffic or surveillance, where vehicles are in constant motion.

The model demonstrates its adaptability by efficiently processing consecutive frames in a video feed. Real-time adaptation is a critical feature, ensuring that the system can keep pace with the rapid movement of vehicles and varying lighting conditions.

III. Testing and results

Comprehensive testing was conducted to evaluate the system’s performance across diverse scenarios.

The efficacy of our ANPR system is comprehensively evaluated through rigorous testing on static images, simulating real-world scenarios encountered in various environments. This challenges the system to adapt and maintain accuracy under different illumination levels, mirroring the unpredictable conditions on roads and streets.

To emulate practical scenarios, the model undergoes testing with license plates positioned at different orientations and potential occlusions. The system’s ability to accurately identify and extract license plate information despite these challenges is a key determinant of its real-world applicability.

Fig. 4. Developed ANPR model testing process

An essential aspect of testing involves evaluating the system’s response time. The efficiency of the ANPR system in quickly, in more less 1 second, and accurately identifying license plates contributes to its practicality for real-time applications such as traffic management and law enforcement. Transitioning to live video feed testing marked a critical milestone. The system showcased real-time capabilities, successfully recognizing license plates on moving vehicles and adapting to dynamic lighting conditions.

IV. CHALLENGES AND FUTURE WORK

Future work may include integrating the developed model into smart parking systems. The system's accuracy and real-time capabilities position it as an ideal candidate for optimizing parking management. Exploration into the integration of the ANPR system into broader security systems is underway. The potential for enhancing surveillance and access control highlights the system's versatility. Considering the continuous evolution of license plate designs, the integration of deep learning models is being explored to further improve the system's adaptability. Another possible future work can be working on energy efficiency aspects of the system with the approach used in these works [19-20].

V. CONCLUSION

In conclusion, the developed ANPR system represents a significant advancement in the accurate recognition of Uzbekistan automobile license plates. By addressing specific challenges associated with the unique characteristics of Uzbekistan plates, the system showcases robust performance in both static images and live video feeds. The successful testing outcomes underscore its potential for practical applications in law enforcement, traffic management, smart parking systems, and security surveillance.

References

[1] do Vale Dalarmelina, Nicole & Teixeira, Marcio & Meneguette, Rodolfo. (2019). A Real-Time Automatic Plate Recognition System Based on Optical Character Recognition and Wireless Sensor Networks for ITS. Sensors (Basel, Switzerland). 20. 10.3390/s20010055.

[2] Y. Shima, "Extraction of number plate images based on image category classification using deep learning," 2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS), Tokyo, Japan, 2016, pp. 19-26, doi: 10.1109/IRIS.2016.8066060.

[3] Patel, Chirag & Shah, D. & Patel, Atul. (2013). Automatic Number Plate Recognition System (ANPR): A Survey. International Journal of Computer Applications (IJCA). 69. 21-33. 10.5120/11871-7665. DOI: 10.5120/11871-7665

[4] S. Azam and M. Islam, 'Automatic license plate detection in hazardous condition', Journal of Visual Communication and Image Representation, Volume 36, Pages 172–186, 2016, http://doi.org/10.1016/j.jvcir.2016.01.015.

[5] Yousri Kessentini, Mohamed Dhia Besbes, Sourour Ammar, Achraf Chabbouh, A two-stage deep neural network for multi-norm license plate detection and

recognition, Expert Systems with Applications, Volume 136, 2019, Pages 159-170, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2019.06.036.

[6] Automatic Number Plate Recognition (ANPR) – 2024 Guide. https://viso.ai/computer-vision/automatic-number-plate-recognition-anpr/ (accessed Feb. 10, 2024).

[7] Junqing Tang, Li Wan, Jennifer Schooling, Pengjun Zhao, Jun Chen, Shufen Wei, Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases, Cities, Volume 129, 2022, 103833, ISSN 0264-2751, https://doi.org/10.1016/j.cities.2022.103833.

[8] Prem, Er & Roy, Prem & Thapa, Arjun & Shrestha, Kumar & Karmacharya, Prasanna & Karna, Rajan. Vehicle Number Plate Recognition and Parking System. International Research Journal of Innovations in Engineering and Technology (IRJIET)ISSN (online): 2581-3048Volume 2, Issue 10, pp 18-23, December-2018

[9] Xianyuan Zhan, Ruimin Li, Satish V. Ukkusuri, Link-based traffic state estimation and prediction for arterial networks using license-plate recognition data, Transportation Research Part C: Emerging Technologies, Volume 117, 2020, 102660, ISSN 0968-090X, https://doi.org/10.1016/j.trc.2020.102660.

[10] Gabriele Guarnieri, Marco Fontani, Francesco Guzzi, Sergio Carrato, Martino Jerian, Perspective registration and multi-frame super-resolution of license plates in surveillance videos, Forensic Science International: Digital Investigation, Volume 36, 2021, 301087, ISSN 2666-2817, https://doi.org/10.1016/j.fsidi.2020.301087.

[11] A. Sasi, S. Sharma and A. N. Cheeran, "Automatic car number plate recognition," 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), Coimbatore, India, 2017, pp. 1-6, doi: 10.1109/ICIIECS.2017.8275893.

[12] Yonten Jamtsho, Panomkhawn Riyamongkol, Rattapoom Waranusast, Real-time license plate detection for non-helmeted motorcyclist using YOLO, ICT Express, Volume 7, Issue 1, 2021, Pages 104-109, doi: https://doi.org/10.1016/j.icte.2020.07.008

[13] M. Satsangi, M. Yadav and P. S. Sudhish, "License Plate Recognition: A Comparative Study on Thresholding, OCR and Machine Learning Approaches," 2018 International Conference on Bioinformatics and Systems Biology (BSB), Allahabad, India, 2018, pp. 1-6, doi: 10.1109/BSB.2018.8770662.

[14] Omar, Naaman & Sengur, Abdulkadir & Al-Ali, Salim. (2020). Cascaded Deep Learning-Based Efficient Approach for License Plate Detection and Recognition. Expert Systems with Applications. 149. 113280. 10.1016/j.eswa.2020.113280.

[15] Gao, Jing & Sun, Lijun & Cai, Ming. (2018). Quantifying privacy vulnerability of individual mobility traces: a case study of license plate recognition data.

[16] Z. Selmi, M. Ben Halima and A. M. Alimi, "Deep Learning System for Automatic License Plate Detection and Recognition," 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), Kyoto, Japan, 2017, pp. 1132-1138, doi: 10.1109/ICDAR.2017.187.

[17] Palaiahnakote Shivakumara, et al, Fractional means based method for multi-oriented keyword spotting in video/scene/license plate images, Expert Systems with Applications, Volume 118, 2019, Pages 1-19, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2018.08.015.

[18] Runmin Wang, Nong Sang, Ruolin Wang, Liangwei Jiang, Detection and tracking strategy for license plate detection in video, Optik, Volume 125, Issue 10, 2014, Pages 2283-2288, ISSN 0030-4026, https://doi.org/10.1016/j.ijleo.2013.10.126.

[19] Asrorbek Eraliev, Uktam Salomov. Development of energy efficient WSN based smart monitoring system. 15th International Conference on Electronics, Computers and Artificial Intelligence, ECAI-2023 Proceedings, 2023. DOI: 10.1109/ECAI58194.2023.10194149

[20] Eraliev A., Bracco G. Design and implementation of zigbee based low-power wireless sensor and actuator network (WSAN) for automation of urban garden irrigation systems (2021) 2021 IEEE International IOT, Electronics and Mechatronics Conference, IEMTRONICS 2021. DOI: 10.1109/IEMTRONICS52119.2021.9422568