License Plate Recognition using Computer Vision and Optical Character Recognition.

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Abstract

The newest generation of object recognition technologies has accelerated the implementation of new Internet of Things (IoT) technologies. Automatic License Plate Recognition (ALPR) systems take advantage of the increasing availability of cameras to improve law enforcement, collect tolls, survey traffic and improve transit patterns, modify maintenance and construction schedules, and for crime deterrence. Providing accurate results given the variety of possible license plate designs and states of origin would allow us to correctly access the data for a vehicle of interest and make it available to the parties interested. Generating those results would require accurate detection of license plates across different weather and lighting conditions and the posterior processing of license plate images including information extraction and proper identification of license plate origin.

1.0 Introduction and Problem Statement

License Plate Recognition (LPR) systems can provide large advantages for law enforcement, surveillance, and surveying applications. Manually gathering this information at a national scale would be impossible due to physical and human constraints. Automating this process significantly benefits society, however, the modern world is presenting new challenges to the current ALRP systems. Variations in weather, lighting, vehicle movement across national and regional borders, customizable license plate designs, and with popular license plate frames often times partially covering registration information provide for endless variations that can affect the effectiveness of such a system. Other illegal modifications, license plate covers, and towing hitches have also exacerbated this issue, although those last ones are not accounted for in the design of this experiment, they all pose challenges to traffic and law enforcement.

ALPR systems have been around for several years but there are still concerns about their effectiveness. The aim of this investigation is to develop an ALPR system that can work across a multitude of environmental and lighting conditions while taking advantage of any other information available to identify the region of origin of the vehicle by using clues such as state logos, mottos, and license plate frame information. The methods in this investigation use pre-trained YOLOv8 models to accelerate convergence, the EasyOCR library to extract alphanumeric data from the images, and other image processing tools to provide an increase in the confidence of predictions.

2.0 Literature Review

The versatility of LPR has made it a frequent subject of study since its first application in 1979 by the British Police (Han et al. 2008). Optical character recognition has many challenges based on differences between license plate styles. Han et al. focused on truck plates and they explore these differences by comparing license plate designs from different states. They show some designs from Florida which contain a dark bar in the center, Kansas which contains extra vertical letters on the left side of the plate, Minnesota plates that contain extra characters on both sides of the registration number; and several other examples of challenging license plates that have low contrast due to color choice (e.g. red letters on a white background or white letters on a light colored background).

Al-batat et al. (2022) explore a modern approach to License Plate recognition; their system includes vehicle detection as an initial step; which will not be considered for the purposes of this project. GPU considerations are also made by Al-batat et al. as there is a large time-sensitive processing component to an effective ALPR system. Their study takes a step-by-step approach to the processing of license plate information. They initially identify the vehicles in each frame; then the vehicle images are cut and separated, the license plates are identified and further separated from the vehicle; and lastly, the characters are detected using YOLOv4-tiny. Due to the fast advancements in the YOLO library architecture, the changes between YOLOv4 and YOLOv8 are significant and will provide an improved solution for the system. They also apply data augmentation techniques to increment their data which allows them to greatly increase the number of uncommon characters, further increasing the accuracy of the system up to 98.22%.

Laroca et al. (2022) generated an ALPR model that was able to take advantage of a high-end GPU to be able to process up to four vehicles at once in real-time achieving an accuracy of 96.9% across eight public datasets. Kumar (2021) explores multiple methods to help better understand the different properties that affect License Plate Recognition and Character Detection within the dataset. Kumar proposes four major groups including color properties, texture properties, edge properties, and other properties based on character detection.

3.0 Data

The data used for this experiment is segmented into several pieces as it contains multiple separate working pieces. For object detection, a set of 433 training images extracted from the work of Aslan Ahmedov from Kaggle that show license plates from around the world was used. Some of the images show concepts of a license plate.

Figure 1: Sample Image from the Automatic Number Plate Recognition training set.

The original goal of this dataset is to simply provide occurrences of license plates so that the frame of a license plate can be detected; therefore not all of the images have real license plates. Some examples of useful plates from this dataset include US, Indian, and European license plates. However, some images do not include license plates at all, and these images were used as the ones that the image processing and models performed the predictions upon. Out of the 433 images in this dataset, only 335 were deemed useful and not duplicated for these purposes after careful consideration and manual labeling of the text on each license plate. However, some of the images that were included had very low resolution, although not low enough for a human to discern the text in the images.

4.0 Research Design and Modeling Methods

The method design proposed for this investigation has three main aspects that will be performed separately. They will be recognizing the license plates, transforming and reorienting the images, and then using optical recognition techniques to recognize the information contained in the license plate.

Recognizing the license plates was done using a pre-trained YOLOv8 model for object recognition that is designed to identify a multitude of objects. This allows for working with less data and computational power.

License plate frame recognition was done by calculating license plate edges with a pre-trained YOLOv8 model to crop and extract only the license plate identified in the image. Image processing was performed by using three different methods: Fourier, Soft, and Binary. The Fourier method provides a representation of the License Plate image in the Frequency Domain as shown in the example below:

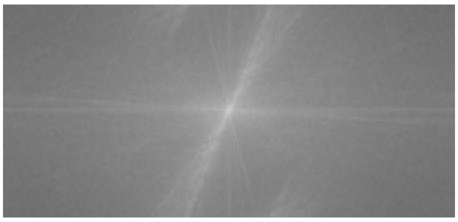

Figure 2: Sample Image with its respective post-cropping Frequency Domain representation after undergoing a 2D Fourier transformation and phase shift.

Figure 3: Input and Output images of the Fournier Method Processing.

The realignment of the image is performed by using information from the frequency domain representation. To calculate the correct alignment of the image, a calculation of the center of mass of the frequency domain array is performed. This is calculated by using the intensity of the pixels and their position to find the best possible angle of rotation. License plate images face the direction of the camera and are tilted or transformed in some way. This provides the algorithm with correct image alignment before processing for extraction of the license plate number/text.

$$F(u,v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$$

Figure 4: Fourier Transformation.

After the calculation of the center of mass of the image, the angle of rotation is calculated from the array and it is then used to rotate the array and recreate the picture as the outcome displayed in Figure 3.

The Soft Processing Method just modifies the image to grayscale and applies a Gaussian blur image filter with an image-scale-dependent radius of 0.2. The Binary Processing Method applies grayscale and modifies the image to a binary representation at a threshold of 100/255 before applying a more intense Gaussian blur to eliminate jagged edges at a scaled radius of 0.75. The images were resampled during processing through all three methods using bicubic interpolation to improve image quality.

The extraction of the text from the images was performed by using a pre-trained model using the EasyOCR library. The prediction with the highest confidence rating based on the results of the model was chosen as the correct prediction and used to choose the method that would be considered to evaluate the predictions of the model.

5.0 Results

Based on the quality of the dataset explored and the large contrast in between the different styles of license plates that were contained within, both the Fourier and Soft processing methods performed at a very similar capacity. The Fourier processing saw a precision of 43.28% from the initial uncropped image to the final prediction while the Soft processing obtained a precision of 44.48% being completely correct. This calculation does not account for instances where the numbers “1” and “0” were confused for the letters “I” and “O” and other such examples where other large text on the license plate accompanied the plate number. Some license plates that included two lines of registration numbers also failed to be processed accurately accounting as artifacts (although the letters may have been obtained, just not in the correct order due to the multiple lines). The binary image processing, however, was the least successful of the three performing at only a 16.12% accuracy. The processing speed of the images in an M1 Macbook Air was 1.108 seconds per image, which although fast, may require further performance improvements and tuning to justify a large-scale application.

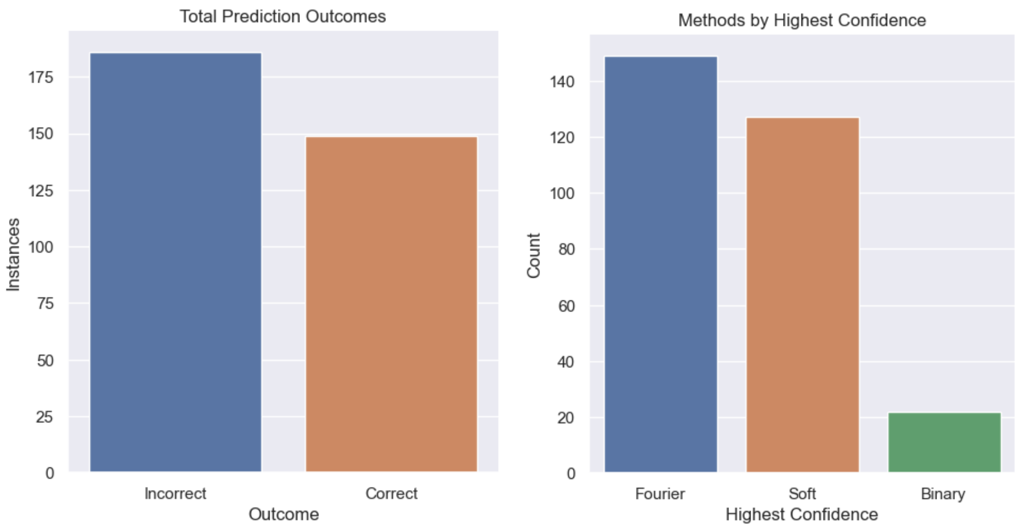

Figure 5: The figure on the left displays the distribution of the outcomes on the total dataset. The figure on the right displays the confidence scores for each of the three different image processing methods.

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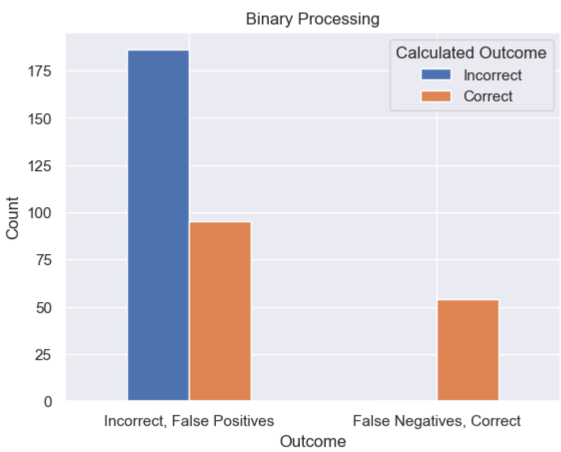

Figure 6: The three processing techniques were compared to understand the impact of instances where overconfidence by any of the models resulted in an erroneous prediction.

The total precision for the model was 44.48% which was equal to the Soft processing method although those final predictions included a significant number of Fourier-method predictions that had the same results yet higher confidence values. Four instances were located in which the Fourier method was correct yet Soft processing was incorrect, while in six other instances, the Soft processing method was correct while the Fourier method was incorrect. This led to a total recall value of 93.71% for the correct predictions due to overconfidence between the two models. The binary predictions lacked confidence and very often provided incorrect predictions while the other two models were correct. The F1-Score calculated was 0.6032.

6.0 Analysis and Interpretation

There was no significant advantage for the model running the Fourier transformations for the prediction as compared to a more basic, simple approach in the Soft method. Upon closer inspection, however, the images processed using Fourier transformations generated higher confidence calculations than the ones processed using the Soft method. This provides a perspective that indeed the Fourier transformations may be useful to reach better transformations. One likely cause of the similar would be the constraints that no padding can bring to images using the Fourier transformations in this case. The images that have more significant angle transformations have some parts cut when this is done without padding. In some cases, specifically for the Indian license plates which generally had longer lengths and shorter widths than the other license plates, this would be more significant than in other types. The confidence scores for the Fourier method had a small difference as compared to the Soft method (84.18% as compared to 84.09%), however, it still yielded the Fourier method an advantage in a considerable amount of images.

The processing speed of images was also considerable given the hardware limitations and the speed of the programming language used (Python) to implement the algorithms. Other algorithms can also process up to four vehicles at a time (LaRoca et. al, 2021). The system in its current shape is not scalable and its focus is rather wide. It is important to consider regional specifications in order to better design this type of license plate recognition system. As useful as it may be to be able to generalize across different regions of the world, it is of utmost importance that the training data contains a large number of elements that are similar to the license plates over which the algorithm is expected to perform. Narrowing down the study and retraining with a large dataset may be one of the most beneficial methods. I still believe in the power of transforming images and restructuring them to better align themselves with training data as a method to improve outcomes.

The great majority of my time was spent getting the Fourier processing of images to work correctly. Oftentimes, it would work perfectly for some images but not for others, which meant that a large amount of time was spent erasing, rewriting, and erasing the same snippets of code. I came to the realization later on that I could calculate the rotation angle in a different way that was not necessarily through a rather naive method of getting the center of mass of the image rather than trying to calculate the angle along the intensities of the lines coming from the center of the image, as I was initially attempting to do using the second circular harmonic of the 2D space of the Fourier transformation.

7.0 Conclusion

I believe that using other datasets that have a consistent license plate structure, shape, font, and color would provide considerably different results. Multiple systems could be devised that implement the classification of plates before attempting to read to be able to adjust for license plate design, color, and format differences. Therefore it would be important to consider this model for other types of applications. The aim was to have a general license plate-detecting algorithm that could correctly read and interpret every possible license plate. However, that is not a realistic goal without a very large dataset and even larger computing power to process and either a team or a large crowd-sourcing effort to correctly annotate thousands of images. The applications of this type of technology are very wide and the obtained accuracy would not justify its application in the real world. The main limitation was the relatively small size of the dataset and the large contrasting differences in between the contained images.

8.0 Directions for Future Work

Reimplementing Padding to the Fourier Method would have prevented NaN values from being generated by the Fourier transformation when processing the images and could have provided better results. Using a larger database of license plate images from a single country/region to train a text recognition model that is more specific to a specific type of font and color of text could provide better results and prevent errors. Another big consideration would be to implement another system that would extract just the registration number from the license plate itself; therefore avoiding other extraneous information such as state or region names, or other types of text that may be in close proximity yet irrelevant to the license plate number itself. Ensuring appropriate systems for data collection would be crucial to any future systems as the quality of the training data was the biggest limiting factor to greater accuracy. One other important addition that has been considered was to add noise to the images to make the system stronger and to help it achieve greater accuracy in adverse environmental situations. Work on this project will continue as I do not feel satisfied with the results and I plan to continue to build upon this project to make it feasible and relevant to the real world. Using the processes that I have learned through the implementation of this model I would like to create a larger model following the same topic of license plate recognition that would draw upon my learnings on this project. It is imperative for me to do so before moving into the field as even with all of what I have learned in this program, it has always been the practical hands-on work from which I have obtained the most.

Appendix

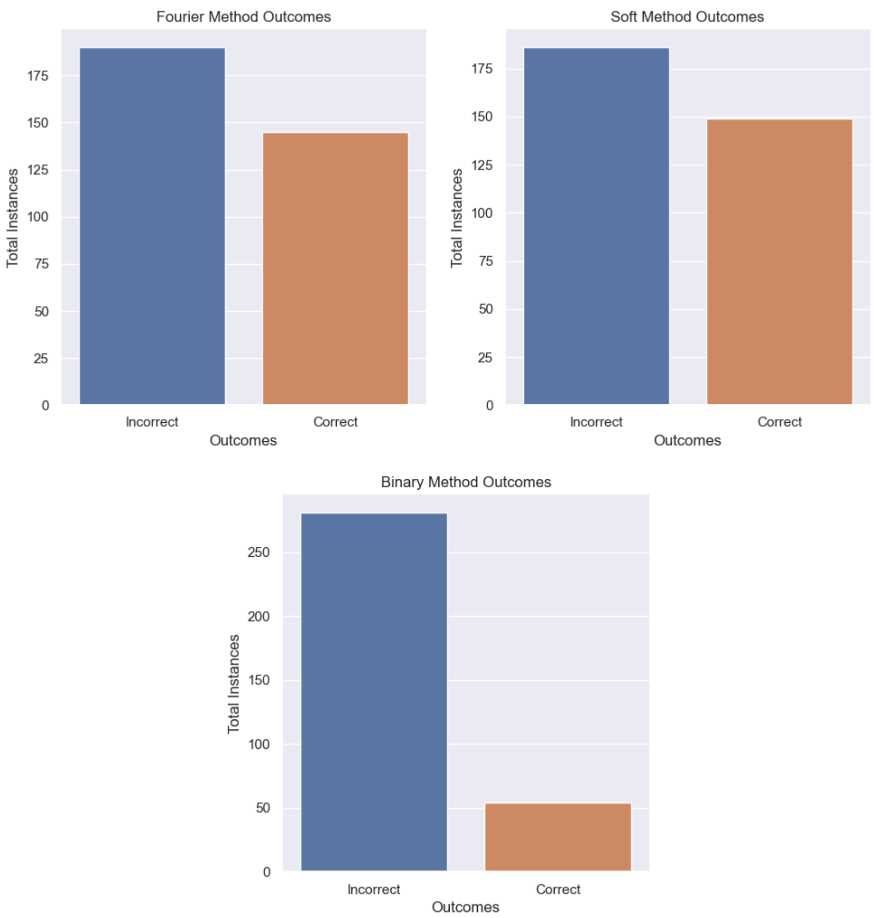

Figure 1: Total Outcomes for all three processing methods.

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