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Deep Learning-Based System for License Plate Recognition In Somalia

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Abstract— Recognizing car license plates plays a vital role in control and surveillance systems. However, manually identifying number plates for parked or passing vehicles is a demanding and time-consuming task. In this paper, we introduce a training-oriented method for vehicle license plate recognition. In contrast to earlier automatic license plate recognition (ALPR) systems, which are constrained by factors like fixed backgrounds, indoor settings, limited vehicle speeds, specific driveways, consistent lighting, or predefined camera-to-vehicle distances, our objective is to develop a resilient recognition model that excels across various lighting conditions and angles [1]. We trained our model using a carefully curated car license plate dataset and the TensorFlow Object Detection API. To assess its performance, we conducted extensive testing on a dataset comprising 24,000 images with diverse colors and lighting conditions. The results demonstrate the efficacy of our approach in achieving precise and robust license plate recognition even in challenging real-world scenarios.

Keywords—Somalia, automatic license plate recognition (ALPR), TensorFlow Object Detection API, character recognition, dataset, traffic management, law enforcement

I. INTRODUCTION

Somalia, located in the Horn of Africa, is a country with diverse landscapes, rich history, and a complex political environment. However, like many developing countries, Somalia is facing challenges in managing its traffic due to the lack of resources and infrastructure. The country is currently experiencing rapid urbanization, resulting in a significant increase in the number of vehicles on its roads. Consequently, traffic congestion, accidents, and violations have become prevalent issues. One of the primary limitations of the traffic management system in Somalia is the absence of automated systems to enforce traffic regulations.

A car license plate serves as a rectangular identification tag that is typically affixed to the front or rear of a vehicle. It bears a unique combination of characters specific to a particular country or city. In terms of designs, colours, sizes, font styles, aspect ratios (the ratio of length to width), and total areas (obtained by multiplying the length and breadth), car licence plates varies significantly between nations.

The layout of the common car licence plates in Somalia consists of two pieces. Along with the Somalian emblem, the upper portion shows the nation's name in both English and Arabic characters. The vehicle's specific string of letters and numbers is displayed in the lower area. This segment consists of two alphabetic characters on the right and four numerals on the left. There are 26 classes of characters in this area, which has a 0 to 9 digit range. As seen in Fig 1, the backdrop of the licence plates is white.

Fig 1 Somali License Plate

There are two separate ways to identify automobile licence plates: manually by human observers, and automatically by computer programmes that can recognise and read car licence plates. The human flexibility of manual licence plate recognition enables for effective identification even in difficult circumstances like partially veiled plates, loud backgrounds, broken characters, or rotated plates. However, manual recognition is a laborious task and presents difficulties in tasks such as cross-referencing with a blacklist database, storing and recalling records of vehicles associated with specific license plates, or calculating parking fees within parking facilities.

In this research project, we suggest creating an ALPR system (automatic licence plate recognition) that makes use of deep learning techniques. This technology uses cutting-edge computational methods to swiftly and reliably scan and comprehend car licence plates in order to support human observers.

ALPR technology has enormous potential for use in a number of areas, including traffic management, parking, access control, automatic toll payment on roads, and the detection of stolen cars using current blacklists.

In order to detect and identify automobile licence plates, several research have been done, demonstrating the significance of this topic. But it's important to recognise that each country's licence plates have different, distinctive characteristics. These characteristics include, among others, the numbering system, colours, typefaces, aspect ratios, character languages, orientations, and plate sizes. Therefore, there is a need for particular study on detecting and identifying licence plates that is customised to the setting of Somalia.

By undertaking this research endeavor, we aim to contribute to the advancement of ALPR technology with a specific focus on detecting and recognizing Somalia license plates. This study will account for the country's unique plate properties, leading to improved accuracy and efficiency in license plate recognition for enhanced applications in various sectors.

The three primary processes of ALPR are generally plate detection, plate segmentation, and plate identification. These procedures are essential for correctly detecting and obtaining licence plate data. The whole outcome may be impacted by any error or inaccuracy in the first plate identification step, which might cascade into the succeeding phases.

The goal of plate detection is to identify the location of the licence plate within the input picture as a whole. This phase is crucial since any errors might have a negative impact on the processes that follow. After a plate has been correctly recognised, plate segmentation kicks in, clearly defining and separating each individual character on the plate.

In the last phase, plate recognition, each segmented alphanumeric character on the licence plate is recognised and understood. The input picture is then overlaid with the identified characters to provide a visual representation of the discovered plate. It is important to keep in mind that the plate detection technique might result in a number of different results, such as no detections, a single detection, or even several detections, particularly when many plates are present in the input picture.

Similarly, plate recognition can yield different results, such as no recognitions, partial recognitions, or complete recognitions, depending on the clarity and quality of the captured characters. By successfully executing these three steps, ALPR systems can effectively detect, segment, and recognize license plates, enabling various applications and functions reliant on accurate license plate information.

This research presents a Somali licence plate identification system that can recognise licence plates from visual sources, especially photographs of moving vehicles, with high accuracy. Beginning with the collection of input from camera-captured photos of the automobile, the system goes through a number of consecutive phases. The system then uses plate detection to find and isolate the licence plate within the input picture, then character recognition to identify each individual character on the isolated plate.

The research makes use of Tesseract and TensorFlow Object Detection to accomplish these goals. In order to find the licence plate in the input file, object detection algorithms are first used. Optical character recognition (OCR) engine Tesseract receives the plate once it has been correctly detected and crops it using the bounding box coordinates. Tesseract analyses the plate picture that has been cropped, detecting and recognising each character after it has been resized.

This paper follows a specific organization. In Section II, a brief analysis of the pertinent literature on ANPR is provided. Section III offers an overview of the ANPR dataset used for collection and testing purposes in this study. The methodology of our proposed ANPR system is detailed in Section IV. Section V presents the findings and discussions regarding the ANPR system. The conclusion is presented in Section VI, while Section VII delves into future directions for this research.

II. LITERATURE REVIEW

The paper by Antar et al. [2] presents a framework for the automatic recognition of Saudi Arabian license plate numbers. They address the challenges specific to Saudi Arabia and propose an approach that combines image processing techniques and machine learning algorithms. Their system includes steps such as license plate localization, character segmentation, and character recognition using a Convolutional Neural Network (CNN) trained on a curated dataset of Saudi license plate images. The authors evaluate the system's performance against existing approaches, demonstrating its effectiveness in accurately recognizing Saudi license plate numbers and achieving high recognition rates.

In their paper Ahmed et al. [3] propose an integrated system that combines automatic number plate recognition (ANPR) technology and machine learning techniques for efficient car towing management. The authors provide a detailed system architecture, including modules for image acquisition, license plate localization, character segmentation, and machine learning-based recognition. The system captures vehicle images, accurately extracts license plate regions, separates individual characters, and utilizes machine-learning algorithms to identify characters and extract license plate numbers.

The authors evaluate the system's performance using real-world datasets and compare its recognition accuracy and processing speed against existing methods. The experimental results demonstrate the superior performance of their ML-powered ANPR system, showcasing its capability for real-time and accurate license plate recognition, surpassing alternative approaches.

Gnanaprakash et al. [4] propose an integrated system for efficient car towing management that combines ANPR technology and machine learning techniques. The system includes modules for image acquisition, license plate localization, character segmentation, and machine learning-based recognition. The authors evaluate the system's performance using real-world datasets and compare it to existing methods, demonstrating its superior real-time and accurate license plate recognition capabilities.

Medvedeva et al. [5] propose a novel approach for license plate recognition that focuses on edge detection techniques. Their system addresses challenges in accurately detecting and recognizing license plates by emphasizing the importance of edge detection in extracting relevant features from license plate images. The authors describe the different steps involved in their system, including preprocessing, edge detection, character segmentation, and character recognition. They apply image enhancement and noise reduction techniques in the preprocessing stage, followed by edge detection to extract

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license plate edges. The license plate is then segmented into individual characters, and character recognition techniques are applied. The authors evaluate their system using a dataset of license plate images and compare it with other methods, demonstrating improved performance in terms of accuracy and computational efficiency.

A unique method for automatic licence plate identification of vehicles utilising a convolutional neural network (CNN) and optimum K-means clustering is presented by Pustokhina et al. [6]. Their approach intends to boost the effectiveness and accuracy of licence plate recognition systems, especially in intelligent transportation systems.

The authors list the essential processes in their procedure, which include character segmentation, character recognition, licence plate location, and picture preparation. While licence plate localization precisely locates and isolates the licence plate location, preprocessing entails noise reduction and picture enhancement. Individual characters are extracted by character segmentation, and a CNN is used to recognise and categorise them.

Using a collection of actual photographs of licence plates, the authors test the effectiveness of their technique. Compared to other approaches, the findings show higher accuracy and efficiency. The ideal K-means clustering and CNN combination results in quicker processing times and higher recognition rates, making it appropriate for use in intelligent transportation systems. The results might have an impact on traffic control, toll collecting, and law enforcement.

Using image processing methods, Varma P et al. [7] provide a novel approach for detecting and identifying Indian automobile registration number plates. Their strategy handles the particular issues with Indian licence plates, such as the varying letter sizes, styles, and backgrounds.

The phases of the authors' method, such as picture preprocessing, number plate localisation, character segmentation, and character recognition, are described. To increase the quality of the images, preprocessing techniques including noise reduction and picture enhancement are used. Character segmentation separates certain characters inside the number plate, whereas number plate localization correctly determines the area the plate occupies. The characters are then recognised and identified using character recognition algorithms.

The authors evaluate their method using a dataset specifically composed of Indian vehicle registration number plates. The experimental results demonstrate the efficacy and accuracy of the proposed approach, even under challenging conditions. This method holds promise for practical implementation in domains such as traffic management, law enforcement, and parking systems.

Henry et al. [8] propose a method for detecting and recognizing license plate characters by combining image processing and machine learning techniques. They enhance the image quality and isolate characters using a segmentation algorithm. A convolutional neural network (CNN) is then trained on a diverse dataset of license plate images from multiple countries to accurately recognize characters with varying styles and formats.

The authors evaluate their method using a dataset of license plate images from different countries. The results demonstrate the effectiveness of their approach in accurately recognizing license plates across nations. It outperforms existing methods and has potential applications in law enforcement, toll collection, and intelligent transportation systems.

Tejas et al. [9] present an efficient license plate recognition system that incorporates Internet of Things (IoT) technologies for smarter interpretation. The system utilizes image processing techniques for preprocessing and extracting license plate information from images. Advanced algorithms for character segmentation and recognition are employed to accurately interpret license plate characters. By integrating IoT capabilities, the system enables real-time data exchange and communication with other devices and systems, enhancing functionality and practicality. The paper highlights the importance of smarter interpretation through IoT connectivity, facilitating intelligent decision-making, automated actions, and improved information sharing. The proposed system offers benefits such as real-time monitoring, remote accessibility, and enhanced data analysis. It has potential applications in traffic management, parking systems, and law enforcement. Overall, the research contributes to the advancement of efficient and intelligent license plate recognition systems by leveraging the power of IoT.

Molina-Moreno et al. [10] propose an efficient scale-adaptive license plate detection system that addresses challenges related to variations in plate size, orientation, and image quality. The methodology involves image preprocessing, a scale-adaptive algorithm, and a novel feature extraction method.

In the preprocessing stage, techniques are applied to enhance image quality. The scale-adaptive algorithm adjusts the search window size to locate license plates of different scales. A novel feature extraction method captures key characteristics of license plates for robust detection in challenging conditions.

Benchmark datasets are used to measure the system's performance, and the outcomes of the experiments show how successful and efficient the suggested strategy is. It works better than currently used techniques, delivering high detection rates while preserving computational effectiveness. Real-time applications in intelligent transportation systems are appropriate for the system.

Li et al. [11] propose a vehicle license plate recognition system that addresses challenges in complex environments. Their system combines the Maximally Stable Extremal Regions (MSER) algorithm and Support Vector Machine (SVM) techniques for accurate and robust license plate recognition. The methodology involves license plate candidate region extraction using MSER, followed by filtering and verification steps to eliminate false positives. The SVM classifier is used for character recognition.

The system's performance is evaluated through experiments using a dataset collected from various complex environments. The results demonstrate its effectiveness in accurately recognizing license plates, even in challenging scenarios with lighting variations, occlusions, and complex backgrounds. The system achieves high recognition rates

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while maintaining computational efficiency, making it suitable for real-time applications in traffic monitoring and law enforcement. This research contributes to improving license plate recognition accuracy in complex environments.

III. DATASET

The collection comprises of 24,000 photos of licence plates from moving and stationary cars. Both daylight and evening photography were used to take these pictures [1]. The dataset is split into three subsets: 88% for training, 8% for testing, and 4% for validation [12] in order to ease model training and assessment. The dataset includes XML-formatted (.xml) annotations for each image that go with it. A graphical user interface (GUI) programme called Labelimg was used in the annotation process to make it easier to designate bounding boxes around objects and create annotation files [13].

Fig 2 showcases a collection of sample images extracted from our extensive car number plate dataset. Careful attention was given to the dataset's construction, ensuring its resilience across a wide range of conditions. This includes diverse variations in fonts, cameras, number plate colors, lighting conditions, backgrounds, as well as varying distances and positions relative to the camera. The images within the dataset are saved in .jpg format and display varying sizes and orientations, mirroring real-world scenarios where cameras are installed at different positions and angles. Furthermore, the images captured by different cameras exhibit variations in quality due to discrepancies in camera specifications, such as optical image stabilization, focal length, bit rate, and autofocus capabilities.

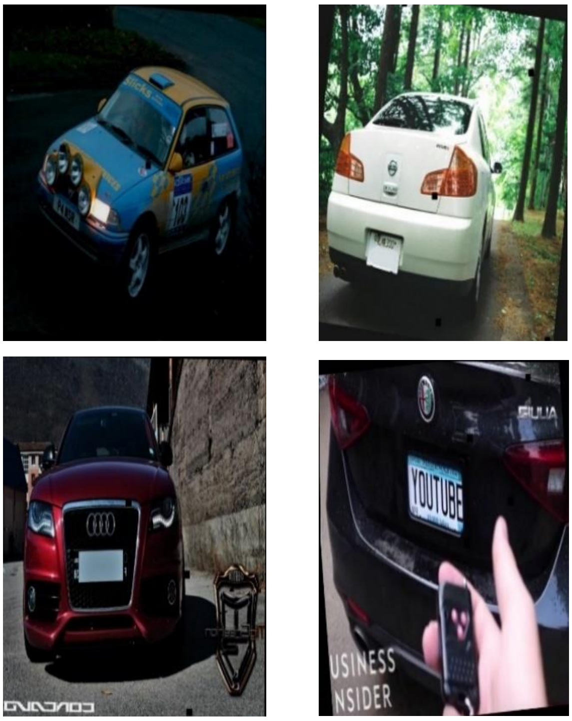

Fig 2 Sample Images of our Dataset

IV. METHODOLOGY

The proposed system utilizes two separate object detection networks to perform different tasks. The first network is specifically designed for plate detection, aiming to accurately identify and locate license plates within an image or video frame. On the other hand, the second network is dedicated to character recognition, focusing on recognizing and extracting alphanumeric characters from the detected license plates. By employing these two networks, the system can effectively tackle the tasks of plate detection and character recognition, contributing to the overall ALPR process.

A. Image acquisition

The initial step in the image processing workflow is to acquire or provide an input image. This can be accomplished through various methods, such as capturing an image using a digital camera connected to a computer or obtaining an image file from different sources, including storage devices or online platforms. In the case of capturing images with a digital camera, the resulting images are typically in the Red Green Blue (RGB) format, which allows for further processing and extraction of the number plate. An example of an RGB image captured during the testing phase is shown in Fig 3. This RGB image serves as the starting point for subsequent image-processing tasks in the system.

Fig 3 Captured RBG Image

B. Plate Localization

Plate localization, also known as license plate localization, is a fundamental process in ALPR systems. Its objective is to accurately identify and locate the license plate within an image or video frame. Plate localization techniques employ various computer vision and image processing algorithms such as edge detection, region-based segmentation, template matching, and neural networks, either individually or in combination.

In the proposed system, plate localization plays a vital role in accurately detecting and localizing the license plate within the image. This step serves as the foundation for subsequent analysis and extraction of important information, including alphanumeric characters, from the license plate. The trained model effectively applies plate localization techniques to identify and locate the license plate within the image, as demonstrated in Figure 4. This highlights the model's proficiency in accurately identifying and localizing this crucial region within the image.

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Fig 4 Detected License Plate

C. Number plate extraction (Region of Interest)

The extraction of number plates, also known as Region of Interest (ROI) extraction, is a critical step in the recognition and analysis of alphanumeric characters on number plates. This process involves isolating and extracting the precise area in an image that contains the number plate. Various techniques, including edge detection, contour analysis, template matching, and machine learning-based methods, can be employed for this purpose. The primary objective is to accurately locate and segment the number plate from the surrounding image, ensuring its structural integrity and legibility for subsequent processing.

To further refine the plate localization process, bounding boxes are utilized to extract the Region of Interest (ROI) from the identified license plate. This step involves isolating and extracting the specific area that encompasses the license plate, enabling enhanced analysis and recognition of the alphanumeric characters present. Fig 5 illustrates the extraction of the ROI using bounding boxes, highlighting the importance of this step in achieving accurate and reliable number plate processing within the overall system workflow

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Fig 5 Region of Interest (ROI)

D. Pre-processing of ROI

The Region of Interest (ROI) extracted from the image undergoes essential pre-processing steps to enhance its quality and prepare it for further analysis. These steps involve operations such as resizing, normalization, noise reduction, and contrast adjustment, among others. The specific techniques and methods employed for pre-processing depend on the specific requirements of the subsequent analysis or feature extraction algorithms being used. By performing pre-processing on the ROI, the overall accuracy and reliability of the subsequent steps in the system are improved.

In the proposed system, the extracted image from the ROI is subjected to a series of pre-processing steps to enhance its quality and suitability for subsequent analysis. These steps include converting the image from RGB to grayscale, reducing noise, and applying border enhancement techniques to improve brightness. Fig 6 provides a visual representation of the original image in RGB format, while Fig 7 illustrates the effects of the pre-processing steps on the extracted image. These pre-processing steps are crucial in optimizing the image for further analysis and achieving accurate and reliable results in the overall system.

Fig 6 Original Image in RGB Format

Fig 7 RGB to Gray Converted Image

E. Character Segmentation

Character segmentation is a crucial operation within an optical character recognition (OCR) system that aims to decompose an image containing a sequence of characters into individual sub-images of each symbol. It plays a vital role in the decision-making process of the OCR system. The objective of character segmentation is to correctly identify and isolate patterns representing individual characters or identifiable units within the image. This decision can be accurate or erroneous.

The segmentation process involves scanning the image for pixels that meet specific criteria. Whenever such a pixel is encountered, its neighboring pixels are examined. If any of the neighboring pixels also meet the criteria, both pixels are considered to belong to the same region. By applying this approach, individual character and number images are obtained through the use of vertical and horizontal scanning techniques.

Fig 8 illustrates an example of plate segmentation, demonstrating the process of isolating individual characters from the image.

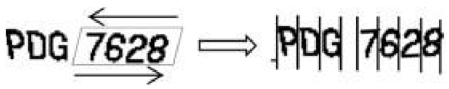


Fig 8 Example of Plate Segmentation

F. Character Recognition

The ALPR system's character recognition phase is an essential element. Techniques for categorising and recognising individual characters taken from the licence plate are used in this step. Optical character recognition (OCR) methods are used to recognise characters by comparing each one to a large database of alphanumeric data. As a consequence of the OCR algorithm's use of pattern-matching algorithms to choose the best match for each character, the characters are recognised and stored in string format.

The recognized characters are then compared with a database of vehicle registrations or authorized plates for further processing. The comparison results in the identification of the vehicle's registration number. Templates are created for each character, encompassing the entire alphabet (A-Z) and digits (0-9), as depicted in Figure 9. These templates serve as references for matching and recognizing individual characters during the OCR process.

Fig 9 Database of Templates

G. OCR (Optical Character Recognition)

OCR, short for Optical Character Recognition, is a technology designed to identify and extract text from digital images. Its primary application is in recognizing text within scanned documents and images. By utilizing OCR software, physical paper documents or images can be transformed into accessible electronic versions that contain editable text.

For instance, when you scan a paper document or photograph using a printer, the resulting digital file typically comprises an image format like JPG, TIFF, or PDF. However, this electronic file still represents only an image of the original document and cannot be easily edited or searched. To overcome this limitation, the scanned electronic document, containing the image, can be loaded into an OCR program.

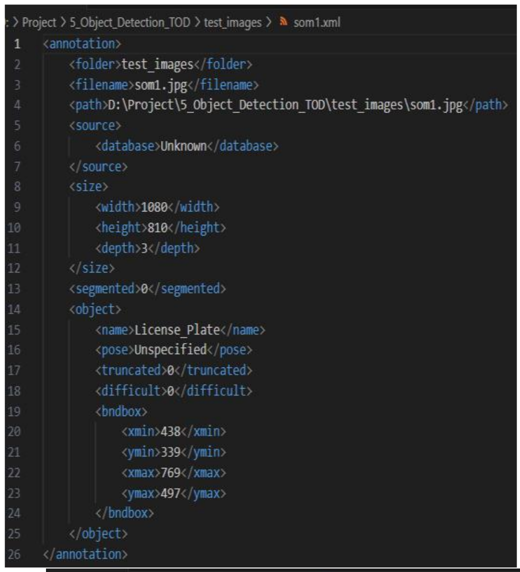
In the proposed system, Tesseract OCR is utilized for character recognition. Tesseract OCR is a widely used open-source OCR engine that employs advanced algorithms to recognize and convert text from images into machine-readable and editable formats. By leveraging Tesseract OCR, the system can accurately recognize the text within the scanned document and convert it into an editable text file.

V. RESULT AND DISCUSSION

The proposed system incorporates two object detection networks, each serving a distinct task. The first network is dedicated to plate detection, utilizing the TensorFlow Object Detection API. Specifically, the pre-trained SSD MobileNet model is employed for the accurate identification and localization of license plates within images or video frames. The second network focuses on character recognition within the detected plates and utilizes the Tesseract OCR Engine for this purpose.

During the training process, Google Colab was used as the platform. The dataset for car number plates comprises a total of 24,000 images, each accompanied by an XML file in the same directory. Within the XML file, crucial information regarding annotations is provided, including labels and the precise coordinates of the bounding box that encloses the objects of interest within the respective image.

These annotations provide valuable data for training the object detection networks, allowing them to learn and recognize license plates and their respective characters accurately.

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    </source>
    <size>
        <width>1080</width>
        <height>810</height>
        <depth>3</depth>
    </size>
    <segmented>0</segmented>
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        <difficult>0</difficult>
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            <ymin>339</ymin>
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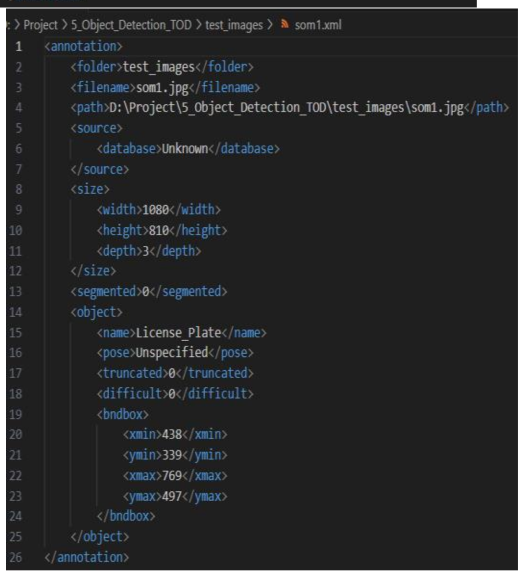


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    </source>
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            <ymin>339</ymin>
            <xmax>769</xmax>
            <ymax>497</ymax>
        </bndbox>
    </object>
</annotation>
```


Fig 10 demonstrates an example of the annotated image, showing the bounding box coordinates for the objects of interest.

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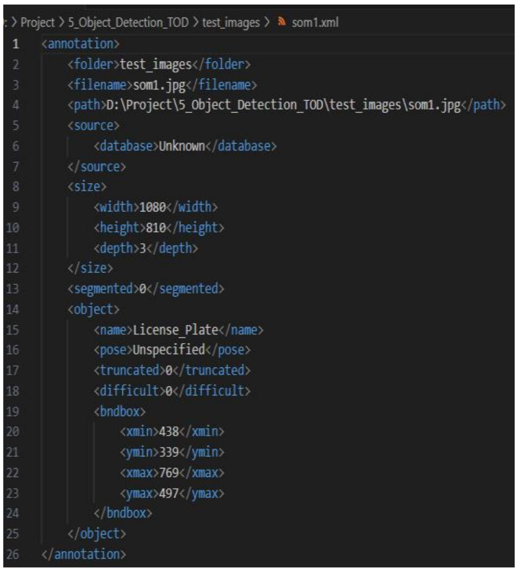

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: > Project > 5_Object_Detection_TOD > test_images > som1.xml
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    <filename>som1.jpg</filename>
    <path>D:\Project\5_Object_Detection_TOD\test_images\som1.jpg</path>
    <source>
        <database>Unknown</database>
    </source>
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        <depth>3</depth>
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            <ymin>339</ymin>
            <xmax>769</xmax>
            <ymax>497</ymax>
        </bndbox>
    </object>
</annotation>
```

Fig 10 Examples of Saved Annotation Files

To bridge the understanding between computers (which interpret labels as numbers) and humans (who prefer labels as names), a label map file (.pbtxt) is created. This file establishes a correspondence between class names and class ID numbers, allowing the trainer to identify and assign appropriate labels to the objects. Fig 11 demonstrates an example of a label map, defining the mapping of class names to class ID numbers.

Furthermore, the system generates two important files: train.record and test.record. These files contain the filenames of the images used for training and testing, respectively. Each filename is listed on a separate line, with the path relative to the images. These files play a crucial role in organizing and associating the image data with their respective annotations during the training and evaluation processes.

```
label_map.pbtxt X
D: > Project > 5_Object_Detection_TOD > data > label_map.pbtxt
item {
    id: 1
    name: 'License_Plate'
}
```

Fig 11 Label Map for Plate Detection

Once the essential settings are configured, the training process is initiated, employing a pre-trained model file specifically designed for the convolutional layers [12]. The training commences with specific parameters as detailed in Table 1. These parameters govern various aspects of the training process, such as the number of iterations, the learning rate, and the batch size. By setting these parameters appropriately, the system can optimize the model's performance and improve its ability to detect and recognize objects accurately.

TABLE 1 PARAMETERS CONFIGURATIONS USED WHILE TRAINING THE DATASET

Parameters	Value
num_classes	1
batch_size	64
width	300
height	300
momentum_optimizer_value	0.9
decay	0.97
learning_rate_base	0.8
total_steps	50000

To ensure accurate object detection, it is important to maintain a consistent and reliable relationship between the objects in the test dataset and the training dataset. This can be achieved by following a general rule that includes considering the relative sizes of the objects. The width and height of the objects in both datasets should be compared using the following ratios:

For object width:

$$(train\_network\_width * train\_obj\_width) / (train\_image\_width) / (detection\_network\_width * detection\_obj\_width / detection\_image\_width)$$

For object height:

$$(train\_network\_height * train\_obj\_height) / (train\_image\_height) / (detection\_network\_height * detection\_obj\_height / detection\_image\_height)$$

To enhance the accuracy and efficacy of object detection, it is crucial to include objects in the training dataset that possess similar class IDs and relative sizes as those in the test dataset. This principle establishes a solid groundwork for training and guarantees the system's ability to accurately detect objects of interest during the detection phase.

After conducting 50,000 iterations of training the ALPR system with a learning rate of 0.8, the achieved results are summarized and showcased in Table 2.

TABLE 2 RESULTS ACHIEVED BY OUR PROPOSED ALPR SYSTEM

ALPR Stages	Accuracy
Number Plate Detection	97.8%
Number Plate Recognition	96%

Fig 12 and Fig 13 depict a compilation of detected images accompanied by their respective accurate predictions. These illustrations exemplify instances where the object detection algorithm effectively recognized and labeled the desired objects with a high level of precision. The correct predictions serve as evidence of the system's capability to reliably detect and classify objects, thereby highlighting its effectiveness in fulfilling the assigned task. By visually presenting these outcomes, one can gain insight into the overall performance and dependability of the object detection system.

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Fig 12 First Predicted Image

Fig 13 Second Predicted Image

VI. CONCLUSION

In conclusion, our proposed system successfully demonstrates the capability to detect the number plate region from an image and extract and recognize the characters. By applying this technology to various images, we can achieve accurate recognition of vehicle number plates. This project aims to automate the number plate detection system for enhanced security purposes. The data obtained from this system can be utilized for multiple purposes, including identifying stolen vehicles and capturing over-speeding vehicles. By replacing the current manual system, this project offers a more efficient and effective solution.

VII. FUTURE SCOPE

The future scope of this project is vast. The automatic vehicle recognition system plays a crucial role in detecting threats, especially in defense applications. Additionally, it can contribute to improving women's security by allowing them to verify their number plate before using a cab or other services. Enhancing the system's robustness can be achieved by employing high-quality cameras with excellent brightness and sharpness. It is recommended that the government takes an interest in developing and implementing this system, as it offers cost savings and environmental benefits when effectively applied in various areas.

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