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Khwopa College of Engineering
Libali, Bhaktapur
Department of Computer Engineering

A FINAL REPORT ON
AUTOMATIC NUMBER PLATE RECOGNITION

Submitted in partial fulfillment of the requirements for the degree

BACHELOR OF COMPUTER ENGINEERING

Submitted by

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CERTIFICATE OF APPROVAL

This is to certify that this minor project work entitled **"Automatic Number Plate Recognition"** submitted by Aabishkar Ghimire(KCE077BCT002), Aaryan Raj Daibagya(KCE077BCT003) and Arun Kumar Shrestha (KCE077BCT010) has been examined and accepted as the partial fulfillment of the requirements for degree of Bachelor in Computer Engineering.

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Abstract

This project endeavors to develop a real-time Automatic Number Plate Recognition (ANPR) system capable of tracking vehicles with specified number plates across multiple camera feeds. To achieve this objective, we employed YOLOv8 [1] for efficient number plate detection. Moreover, we devised a novel algorithmic architecture to rectify skewness and perspective distortion commonly encountered in number plate images. Subsequently, contour analysis was utilized for precise segmentation of characters within the number plate region. For character classification, Support Vector Machine (SVM) was employed.

The system comprises an interactive frontend interface, a robust database for storing and retrieving relevant information, and seamless integration with the backend for efficient processing. By integrating multiple cameras, our system aims to enhance surveillance capabilities and aid in law enforcement efforts.

Keywords: *Automatic Number Plate Recognition, Convolutional Neural Network, Machine Learning*

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List of Abbreviation

Abbreviations	Meaning
ANPR	Automatic Number Plate Recognition
CNN	Convolutional Neural Network
YOLO	You Look Only Once
SVM	Support Vector Machine
OCR	Optical Character Recognition
BOLO	Be On the LookOut
OpenCV	Open Source Computer Vision Library

Chapter 1

Introduction

1.1 Background Introduction

The Automatic Nepali Number Plate Recognition (ANPR) system represents a significant technological advancement in the field of vehicle identification and tracking. With the increasing need for efficient traffic management, enhanced security measures, and improved law enforcement capabilities, ANPR systems have emerged as indispensable tools in modern transportation infrastructure.

The concept of ANPR systems originated from the necessity to automate the tedious and error-prone process of manually recording vehicle license plate numbers. Traditionally, law enforcement agencies and traffic authorities relied on manual interventions to identify vehicles, leading to inefficiencies, delays, and inaccuracies in data collection. Moreover, the growing volume of vehicular traffic and the proliferation of surveillance cameras necessitated the development of automated solutions capable of processing large quantities of image data in real-time.

Over the years, advancements in image processing, computer vision, and machine learning technologies have paved the way for the development of sophisticated ANPR systems capable of accurately and rapidly recognizing license plates under various conditions. These systems leverage a combination of techniques, including image segmentation, feature extraction, and pattern recognition, to detect and extract license plate information from digital images or video streams.

In the context of Nepal, where vehicular traffic continues to grow rapidly, and the need for efficient traffic management and law enforcement is paramount, the implementation of an ANPR system holds immense potential. By automating the process of vehicle identification and tracking, ANPR systems can significantly enhance the efficiency of traffic operations, improve security measures, and enable proactive law enforcement interventions.

In this project, we present the design, development, and implementation of an ANPR system tailored specifically for Nepali license plates. We discuss the methodologies, algorithms, and technologies employed in the system, along with the expected outcomes and potential implications for transportation infrastructure and public safety in Nepal. Through this endeavor, we aim to contribute to the advancement of transportation systems and enhance the quality of life for citizens through innovative technological solutions.

1.2 Motivation

When we proposed our project, we noticed a significant gap in surveillance infrastructure in Nepal. Law enforcement relied solely on manual methods to inspect camera feeds and patrol areas, resulting in missed opportunities to identify wanted vehicles. Recognizing the need for a more efficient solution, we were motivated to develop a real-time Automatic Number Plate Recognition (ANPR) system.

Our objective was clear: to streamline vehicle identification and tracking processes for law enforcement. By automating ANPR, we aimed to eliminate the inefficiencies associated with manual inspection, ultimately saving time and resources. Our project sought to empower law enforcement agencies in Nepal with a tool that could enhance public safety and security by facilitating quicker and more accurate identification of vehicles of interest.

1.3 Problem Statement

In Nepal, the absence of an effective Automatic Number Plate Recognition (ANPR) system poses significant challenges for law enforcement agencies. Manual inspection of camera feeds and patrol areas has proven to be time-consuming and inefficient, leading to missed opportunities in identifying wanted vehicles. This reliance on outdated methods hampers the ability of authorities to swiftly respond to security threats and enforce traffic regulations.

Furthermore, the lack of a comprehensive ANPR system exacerbates the strain on limited resources and manpower. Without automated plate recognition capabilities, law enforcement efforts are hindered, resulting in increased operational costs and reduced effectiveness in crime prevention and detection.

To address these challenges, there is an urgent need for the development and implementation of a real-time ANPR system tailored to the specific requirements of Nepal's law enforcement agencies. Such a system would not only streamline vehicle identification processes but also enhance the overall security infrastructure, ultimately contributing to a safer and more secure environment for all citizens.

1.4 Objective

The main objective of this project is:

- To develop real-time Automatic Number Plate Recognition (ANPR) system with multi-camera support.

1.5 Scope and Applications

The major applications of this project are:

- Effective traffic management
- Law enforcement

Chapter 2

Literature Review

The field of Automatic Number Plate Recognition (ANPR) has seen significant advancements globally, with numerous studies focusing on adapting techniques to various languages and scripts. In the context of Nepali ANPR, however, the literature is relatively limited but emerging.

2.1 Automatic Nepali number plate recognition with support vector machines

In this paper [2], for detection of Number Plates is done by HSV Color Space Conversion and Color Masking so the color red is targeted and masked then its contour is performed with Aspect ratio test and Profile test.The character Segmentation is done by skew correction then analyzing their projection .OCR is done by support vector machine .Features are extracted from the image using the HOG descriptor. The accuracy of complete number plate labeling experiment was 75%.

2.2 CNN based System for Automatic Number Plate Recognition

In this Paper [3], the focus was on Number Plate Segmentation and Character Segmentation using distinct methodologies. Number Plate Segmentation was achieved by identifying distinct regions based on color, leveraging the unique characteristics of number plate colors to separate them from the background. For Character Segmentation, the researchers utilized an Inception-ResNet model to accurately isolate individual characters from the segmented number plates. Despite the overall accuracy of the trained models being estimated to be over 83%, the main challenge remained in improving the segmentation accuracy of the characters themselves. This aspect is crucial for ensuring the reliability and precision of the entire automatic number plate recognition system. Addressing this challenge would likely involve further refinement of the segmentation algorithms and potentially exploring additional techniques to enhance character segmentation accuracy.

2.3 An Approach to Enhance the Character Recognition Accuracy of Nepalese License Plate

In the paper [4], Number Plate Segmentation was done using YOLOv3, They utilized YOLOv3, to detect and segment number plates from images. Following this initial segmentation step, they employed horizontal and vertical projection profiles to further refine the segmentation process at the character level. By analyzing these profiles, they were able to separate individual characters effectively. This meticulous approach resulted in an impressive character accuracy rate of 92%, showcasing the effectiveness of their segmentation and recognition methodology.

2.4 Vehicle Number Plate Recognition and Parking System

In this paper [5], methodology for Plate Region Extraction and Optical Character Recognition (OCR) was done utilizing image binarization and correlation methods. Plate region extraction was accomplished through image binarization, a process that converts the input image into a binary format, where pixels are classified as either foreground or background based on certain criteria such as intensity thresholding. This binary representation facilitated the isolation of the number plate region from the background, laying the foundation for subsequent OCR tasks. For OCR, the correlation method was used which involves comparing the extracted plate region with predefined templates of characters. By calculating the correlation between the plate region and each template, the characters present on the number plate could be identified. This approach leverages pattern recognition techniques to recognize characters based on their similarity to predefined patterns, enabling efficient and accurate character recognition.

2.5 A Review of Automatic Number Plate Recognition

In this project [6], character recognition was achieved using Google Tesseract, a widely-used open-source OCR engine known for its accuracy in recognizing text from images. Leveraging the capabilities of Tesseract, the system could accurately identify and interpret characters present on the number plates extracted from images.For number plate detection, the project utilized YOLOv5, a state-of-the-art object detection algorithm renowned for its speed and accuracy in detecting objects within images. By employing YOLOv5, the system could efficiently locate and extract the regions containing number plates from the input images, providing the necessary input for subsequent character recognition.

S.N	Title	Summary
1	Automatic Nepali number plate recognition with support vector machines	In this paper, License Plate Localization ;HSV Color Space Conversion and Color Masking with contour, feature extractor; HOG descriptor and classifier; SVM algorithm is used on 2033 character datasets training images with model accuracy of 75%. Problem ; Accuracy of the character recognition is greatly influenced by the segmentation accuracy of the characters
2	CNN based System for Automatic Number Plate Recognition	In this project, Number Plate Segmentation;identifying distinct regions based on color ,character segmentation; Inception-ResNet model with overall accuracy of the trained models estimated to be over 83%.problem; segmentation accuracy of the characters
3	An Approach to Enhance the Character Recognition Accuracy of Nepalese License Plate	In the paper ,Number Plate Segmentation;YOLOv3,Character Segmentation ; horizontal and vertical projection profiles ,character accuracy;92%
4	Vehicle Number Plate Recognition and Parking System	In this paper,Plate region extraction;image binarization, OCR;correlation method ;
5	A Review of Automatic Number Plate Recognition	In this project character recognition; Google Tesseract,number plate detection; YOLOv5

Table 2.1: Review Matrix with Research Papers and summary of corresponding papers.

Chapter 3
Requirement Analysis

3.1 Software Requirement

Our ANPR system requires the following software:

1. Python
2. Star UML
3. Visual Studio Code
4. Google Colaboratory
5. CUDA
6. Git
7. Slack
8. XAMPP

3.2 Hardware Requirement

The project required following hardware requirements:

1. Windows Computer with NVIDIA Graphics Card (Cuda Enabled) and 8GB RAM.
2. Camera(s)

3.3 Functional Requirement

The successful operation of the Automatic Nepali Number Plate Recognition (ANPR) system relies on fulfilling various functional requirements. These requirements encompass the system's capabilities and operations, ensuring accurate and efficient license plate identification and processing. The key functional requirements include:

3.3.1 Image Acquisition

The system must be equipped with high-quality cameras capable of capturing clear and detailed images of vehicles and their license plates. These cameras should be strategically positioned to cover target areas effectively, ensuring optimal image capture under diverse environmental conditions.

3.3.2 License Plate Localization

Develop algorithms to precisely locate and isolate license plates within captured images. The localization process should account for variations in lighting, perspective, and plate orientation, enabling accurate extraction of license plate regions for further processing.

3.3.3 Character Segmentation

Implement robust segmentation algorithms to extract individual alphanumeric characters from localized license plate images. The segmentation process should accurately delineate characters while minimizing noise and artifacts, facilitating reliable character recognition.

3.3.4 Character Recognition

Develop classification models capable of accurately recognizing and interpreting segmented characters. The recognition algorithms should account for variations in character size, style, and orientation, ensuring consistent and reliable identification of alphanumeric characters.

3.3.5 Real-time Processing

Ensure that the system can process captured images in real-time, enabling prompt identification and analysis of license plates as vehicles pass through monitored areas. Real-time processing is essential for timely detection of vehicles of interest and rapid response to security threats or traffic violations.

3.3.6 Multi-camera Support

Enable the system to handle inputs from multiple cameras simultaneously, allowing for comprehensive surveillance coverage across different locations. The system should coordinate data from multiple sources and trigger alerts or notifications upon detecting vehicles matching specified criteria.

3.3.7 User Interface

Design an intuitive and user-friendly interface for system administrators to monitor, manage, and configure the ANPR system. The interface should provide access to system settings, analytics, and reporting tools, facilitating efficient operation and decision-making.

3.4 Non-Functional Requirement

In addition to the functional aspects, the successful implementation of the Automatic Nepali Number Plate Recognition (ANPR) system also relies on meeting various non-functional requirements. These requirements define the system's qualities, attributes, and constraints, ensuring its overall effectiveness, performance, and usability. The key non-functional requirements include:

3.4.1 Accuracy

The ANPR system must achieve a high level of accuracy in license plate localization, character segmentation, and recognition processes. The accuracy rate should meet or exceed specified performance metrics to minimize false positives and ensure reliable identification of vehicles and their license plates.

3.4.2 Speed

The system should operate with minimal latency and processing time to enable real-time identification and analysis of license plates. Speed is essential for timely detection of vehicles, facilitating prompt responses to security incidents, traffic violations, and other critical events.

3.4.3 Scalability

The ANPR system should be scalable to accommodate increases in data volume, camera inputs, and processing requirements over time. Scalability ensures that the system can effectively handle growing demands and adapt to evolving operational needs without compromising performance or reliability.

3.4.4 Robustness

The system must demonstrate robustness in diverse environmental conditions, including variations in lighting, weather, and vehicle movement. Robust algorithms and components are essential for maintaining system functionality and accuracy under challenging operating conditions.

3.4.5 Security

Ensure that the ANPR system incorporates robust security measures to protect sensitive data, prevent unauthorized access, and mitigate potential cybersecurity threats. Security protocols should comply with industry standards and regulatory requirements to safeguard system integrity and user privacy.

3.4.6 Usability

Design the system interface and user interactions to be intuitive, accessible, and user-friendly for administrators and operators. Usability considerations include clear navigation, informative feedback, and customization options to enhance user satisfaction and productivity.

3.4.7 Reliability

The ANPR system must demonstrate high reliability and availability to support continuous operation and critical applications. Reliable performance is essential for maintaining surveillance coverage, responding to security incidents, and facilitating law enforcement activities without disruptions or downtime.

3.4.8 Maintainability

Facilitate ease of maintenance and system updates through modular design, clear documentation, and standardized procedures. Maintainability ensures that administrators can troubleshoot issues, apply updates, and optimize system performance efficiently over time.

Chapter 4

Feasibility Study

4.1 Economic Feasibility

The economic feasibility of the ANPR system primarily revolves around the cost implications associated with its development and deployment. Fortunately, the project's economic feasibility is promising as it primarily requires computational resources. The dataset necessary for training the system can be obtained from various sources, including online repositories or manually captured images of Nepali number plates. Additionally, the computational power required for training and deployment is available within the project team's existing infrastructure, including personal laptops and high-performance computers available at the institution. Therefore, the project is economically feasible, as it does not entail significant upfront costs or ongoing expenses beyond existing resources.

4.2 Technical Feasibility

Technical feasibility assesses the project's feasibility from a technological perspective, considering factors such as data availability, algorithm complexity, and computational requirements. The ANPR system's technical feasibility is robust, given the availability of labeled images of Nepali number plates for training purposes. Although preparing the dataset and labeling images may involve some complexities, such as classifying license plates and categorizing vehicles, these challenges are manageable with proper planning and execution. Additionally, training the ANPR system with the dataset requires substantial computational power, which can be fulfilled using high-performance computers equipped with suitable processors and graphics processing units (GPUs). Therefore, the project's technical feasibility is high, with the necessary resources and expertise available to overcome potential challenges.

4.3 Operational Feasibility

Operational feasibility evaluates the practicality of implementing and using the ANPR system within the intended operational environment. In the case of the ANPR system, operational feasibility is favorable, as the system can be seamlessly integrated into existing infrastructure and operational workflows. Once trained with labeled data using neural network models, the ANPR system can efficiently process input images or videos and provide accurate license plate recognition results. The user interface of the system will be intuitive and user-friendly, enabling users with basic technical knowledge to operate it effectively. Moreover, the system's real-time processing capabilities and multi-camera support ensure its suitability for monitoring multiple locations simultaneously. Therefore, the ANPR system's operational feasibility is high, with minimal barriers to implementation and adoption.

Chapter 5

System Design and Architecture

We developed a Automatic Number Plate Recognition (ANPR) system which takes continuous camera feed from multiple cameras as its input and notifies the authorities if a wanted number plate is seen in any of the camera feed.

5.1 Use Case Diagram

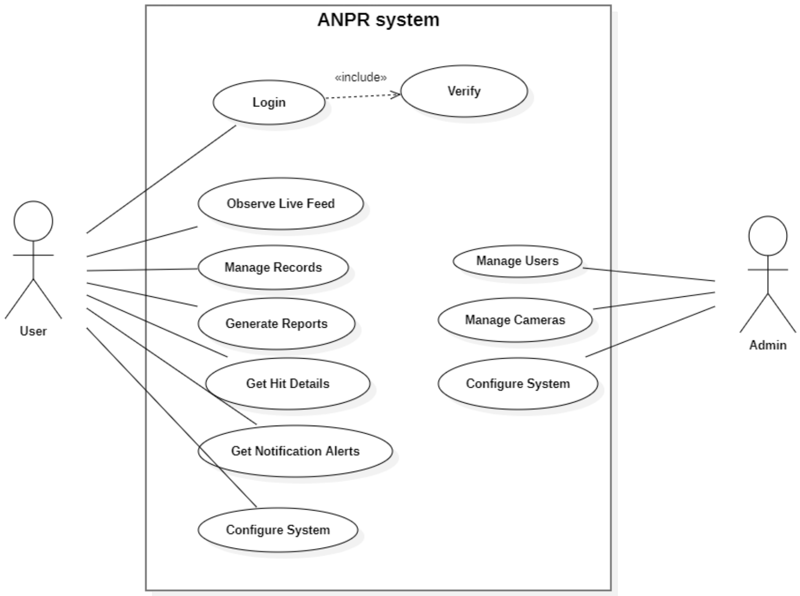


Figure 5.1: System Use Case Diagram

User acts as a primary actor and has ability to create new records, generate reports, get the search hit details, get hit alert. Admin can configure the system including the camera, users, and other system settings. After new record has been created the ANPR system has to actively look for the number plate in all camera feed. If found in any camera feed, immediate alert should be given to authorities along with additional hit details such as frame, hit location, hit time, details about the record as well as the hit history of the number plate stored in the database.

5.2 Block Diagram

Figure 5.2: Block Diagram of Number Plate Recognition (NPR) Module

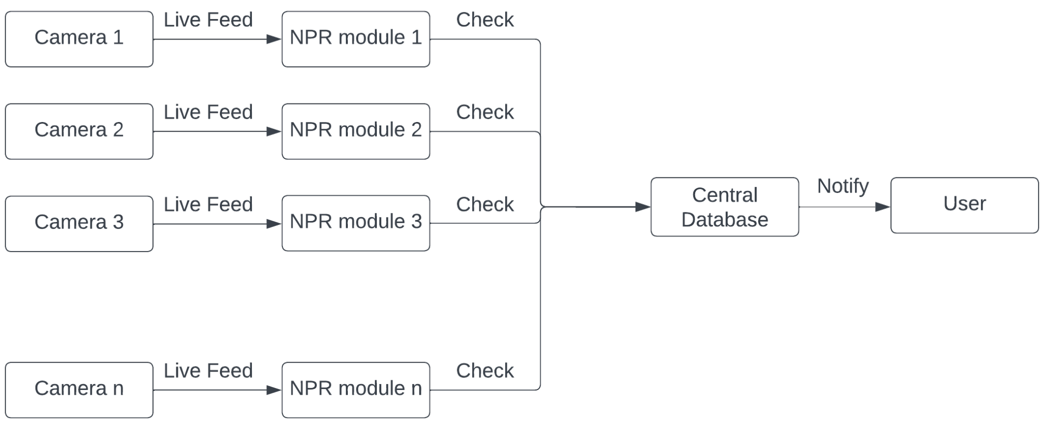


Figure 5.3: Block Diagram of overall ANPR system

5.3 ER Diagram

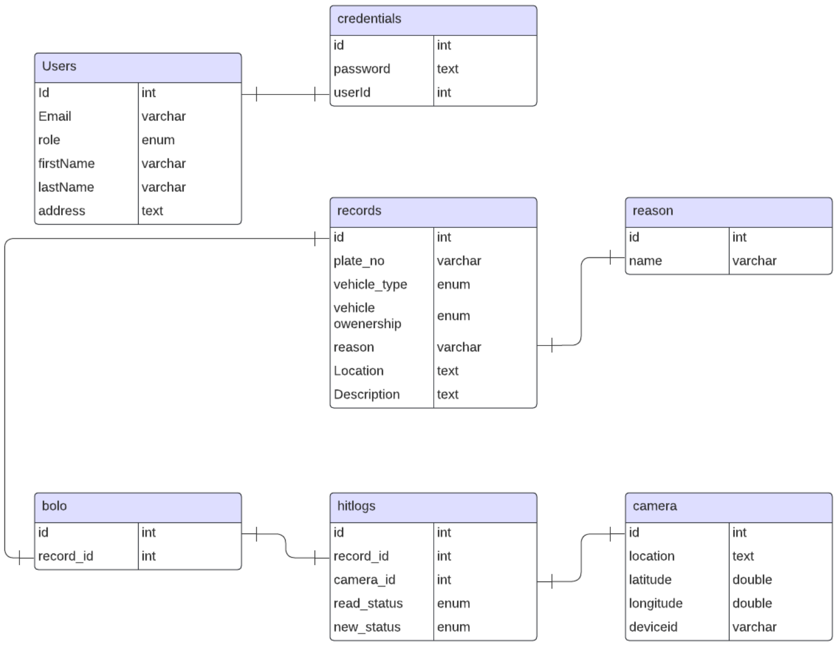


Figure 5.4: ER Diagram

5.4 Flow Chart

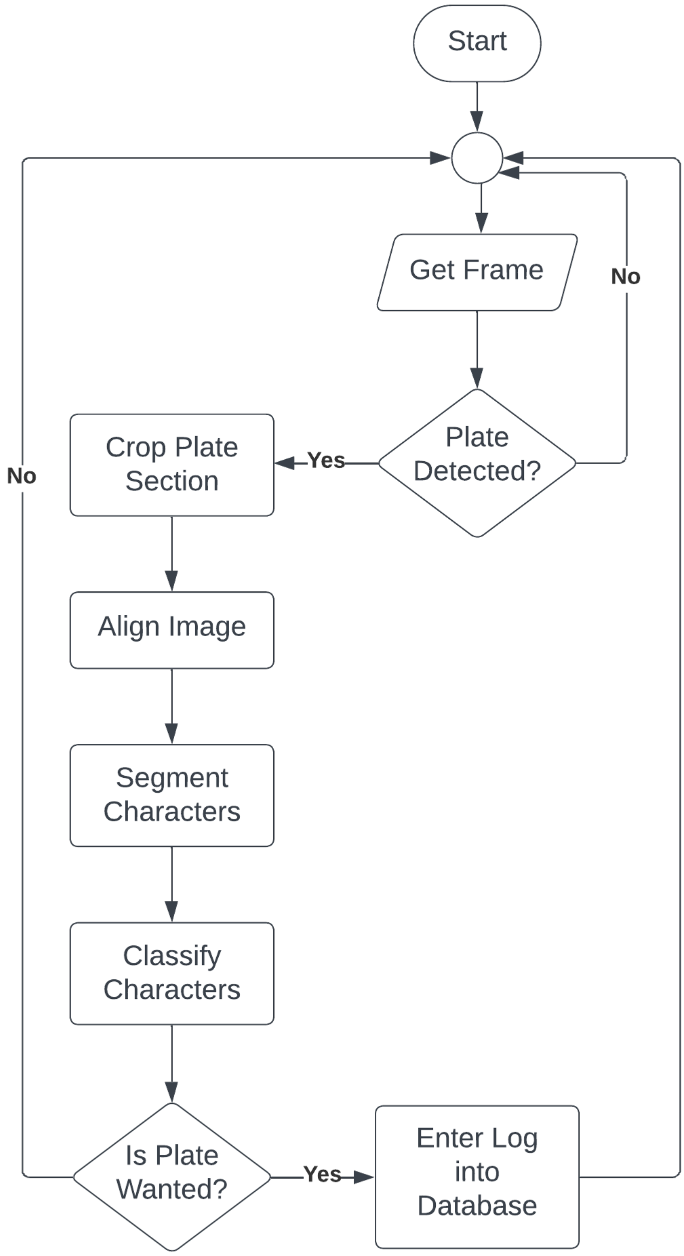


Figure 5.5: Flow chart for NPR module of ANPR system

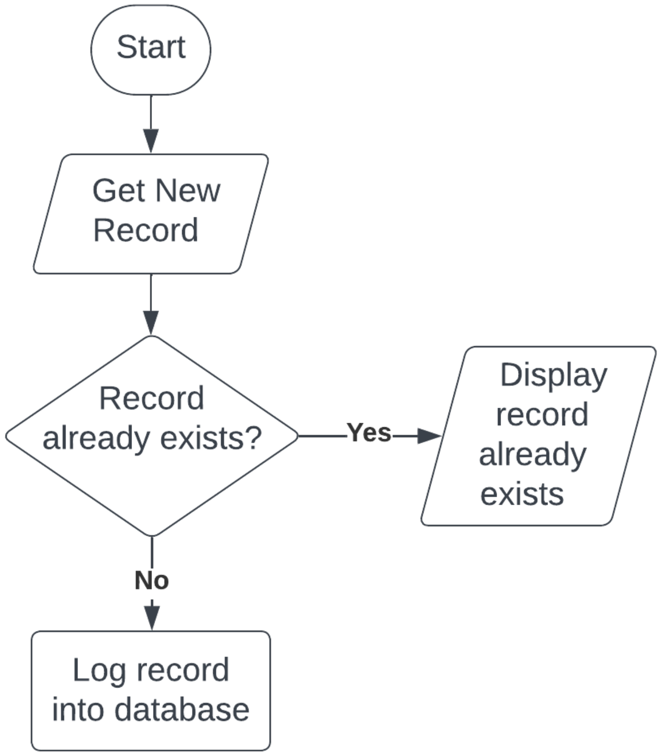


Figure 5.6: Flow chart for Management module of ANPR system

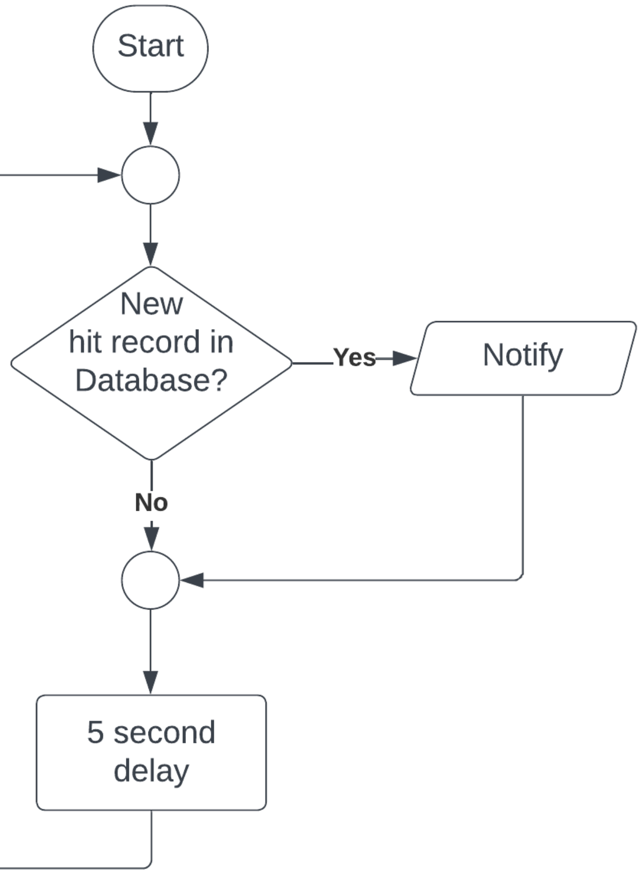


Figure 5.7: Flow chart for notification module of ANPR system

Chapter 6

Methodology

6.1 Development Aproach

The Agile development approach is a dynamic and customer-centric methodology that prioritizes adaptability, collaboration, and continuous improvement throughout the software development lifecycle. Characterized by its iterative and incremental nature, Agile breaks down the development process into manageable iterations, ensuring that each iteration delivers a potentially shippable product increment. Flexibility is a core tenet, allowing Agile teams to readily respond to changing requirements, evolving priorities, and shifts in the business landscape. Customer collaboration is integral to the Agile philosophy, emphasizing regular and close interaction with stakeholders to incorporate feedback and align development efforts with customer expectations. Cross-functional teams, comprising members with diverse skill sets, facilitate efficient communication and collaboration. Continuous delivery is a key goal, enabling the rapid and consistent delivery of valuable software increments. Agile embraces change, recognizing that requirements are subject to evolution, and the development process should accommodate such changes without undue disruption. Regular reflection and improvement, often facilitated through retrospective meetings, underscore Agile's commitment to refining processes and enhancing team performance.

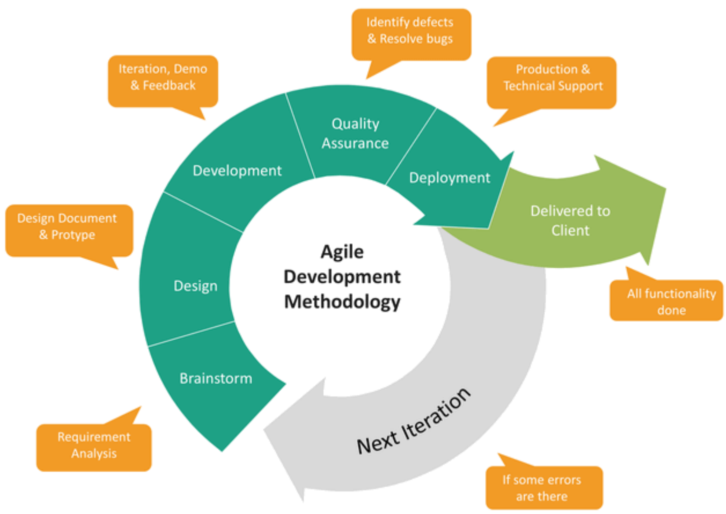


Figure 6.1: Agile Model for Software Development

source: https://www.archbee.com/blog/technical-documentation-waterfall-vs-agile

6.2 Dataset Preparation

The dataset for training the Automatic Number Plate Recognition system underwent a comprehensive preparation process, involving the collection of raw images, manual annotation, character dataset generation, and manual classification of segmented characters.

6.2.1 Collection of Raw Images

A total of 3014 raw images of Nepali number plates were gathered manually and from online source [7]. These images provided a diverse representation of Nepali number plates in various contexts and environmental conditions.

6.2.2 Augmentation of Raw Images

Following the collection of raw images, a subset of the images underwent augmentation to enhance the robustness of the model in detecting skewed number plates. This augmentation involved randomly rotating the images by angles within the range of 1 to 25 degrees. By introducing this variation, the model gains exposure to skewed number plates, thereby improving its ability to accurately detect and recognize number plates across diverse orientations and environmental conditions.

Figure 6.2: Example of a raw image (left), its corresponding augmented image rotated clockwise (center), and its corresponding augmented image rotated anticlockwise (right).

6.2.3 Manual Annotation

Each image in the dataset underwent manual annotation using an annotating tool [8]. Bounding boxes were meticulously placed around the number plates within the images to facilitate supervised learning.

The annotation format for YOLOv8 follows the convention of normalized coordinates. Each annotation consists of five values: class, normalized center coordinates (x, y), normalized width (w), and normalized height (h). These values represent the position and size of the bounding box relative to the dimensions of the image. This format allows for consistent representation of object locations across different image resolutions and aspect ratios, facilitating efficient training and inference with the YOLOv8 model.

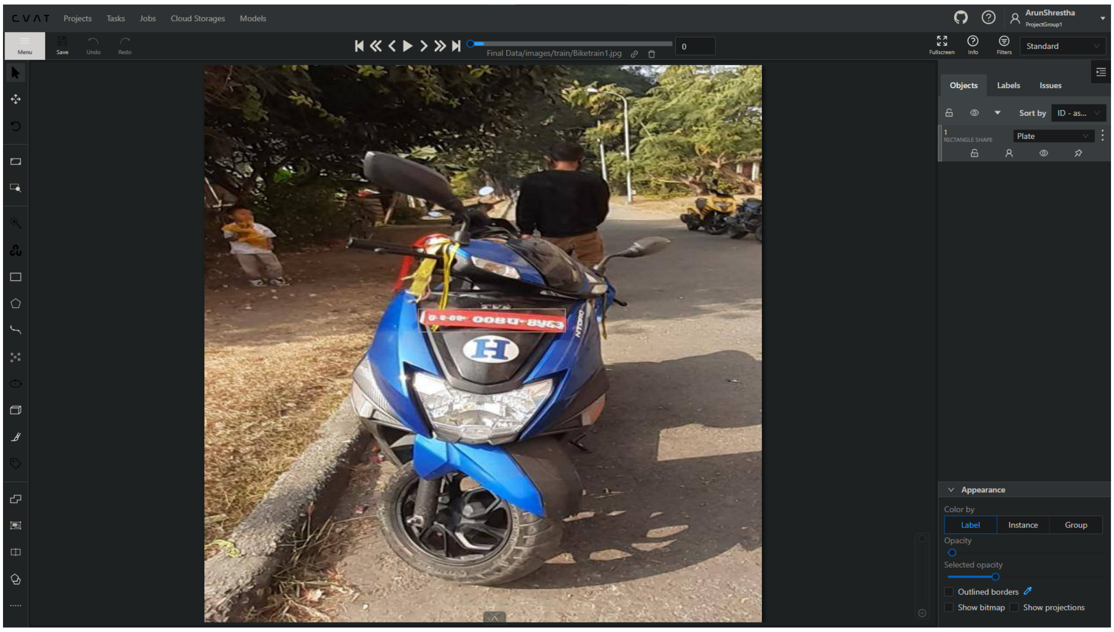


Figure 6.3: Example of manual annotation of raw images.

0	0.515766	0.458234	0.263563	0.041250
class	centerX	centerY	width	height

Figure 6.4: Example of a bounding box annotation (left) and its corresponding annotation format (right).

6.2.4 Character Dataset Generation

To facilitate character recognition, we created a character dataset. Utilizing YOLOv8 object detection, we trained the model to identify number plates within images. Additionally, we developed a character segmentation algorithm. Combining both approaches, we autonomously segmented characters from the annotated dataset images. This process yielded 5720 segmented character images.

Figure 6.5: Left: Example of image data. Right: Example of segmented character data.

6.2.5 Manual Classification of Segmented Characters

The segmented character images were manually classified into their respective categories. Each character was meticulously categorized based on its alphanumeric representation. This manual classification ensured the accuracy and reliability of the character dataset for training purposes.

Class	Number of Dataset
0	464
1	637
2	523
3	421
4	407
5	361
6	378
7	397
8	341
9	425
ba	614
cha	522
ga	1
gha	2
ja	9
kha	19
ko	4
lu	1
pa	191
ra	3
Total	**5720**

Table 6.1: Dataset Classification by Class

6.2.6 Dataset Splitting

The dataset was divided into training and testing sets using an 80:20 ratio, ensuring that 80% of the data was allocated for training the model, while the remaining 20% was reserved for testing its performance. The table below illustrates the distribution of images between the training and testing sets:

Purpose	Dataset	Number of Images	Percentage
Detection	Training	2412	80%
	Testing	602	20%
Classification	Training	4576	80%
	Testing	1144	20%

Table 6.2: Distribution of Images between Training and Testing Sets

6.3 Number Plate Recognition Pipeline

6.3.1 Number Plate Localization

For the task of number plate localization, the system utilizes the YOLOv8 object detector developed by Ultralitics. Specifically, the Nano version of YOLOv8 is employed to ensure optimal performance while conserving computational resources. This model is trained on the prepared dataset, consisting of raw images of Nepali number plates, using annotated bounding boxes for localization.

The training process involves training the YOLOv8 Nano model for 600 epochs on the dataset. During training, the model learns to accurately identify and localize the regions of interest containing Nepali number plates within the input images. By leveraging deep learning techniques and state-of-the-art object detection algorithms, the system achieves robust and reliable localization of number plates in diverse environmental conditions.

6.3.1.1 Training Metrics

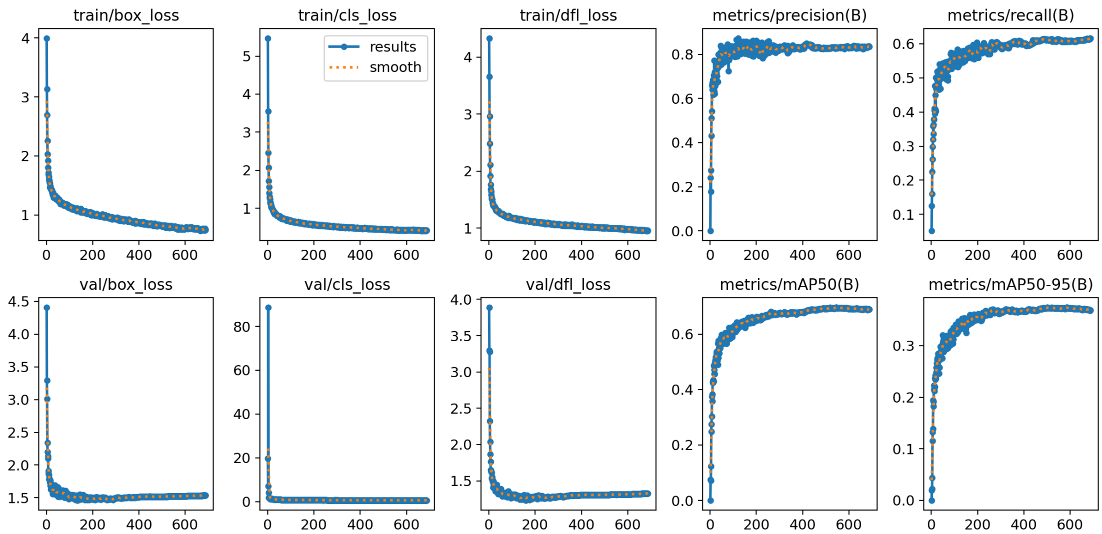
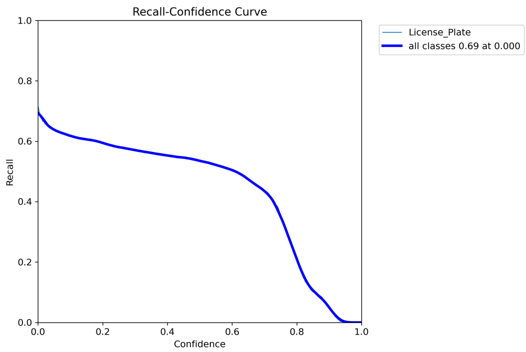
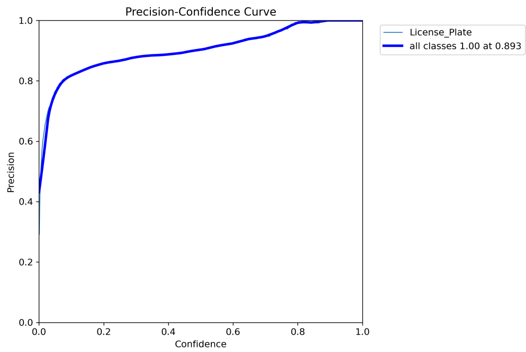


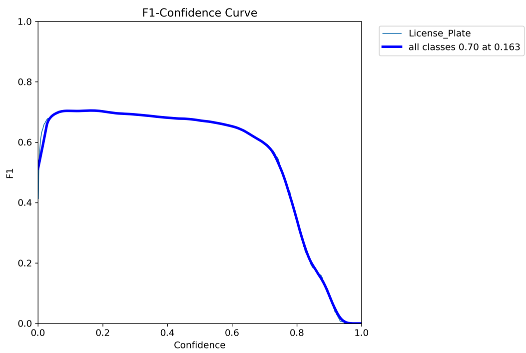
Figure 6.6: Training and Validation losses



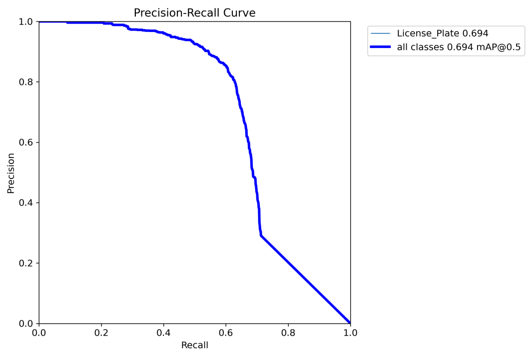
(a) Recall-Confidence Curve



(b) Precision-Confidence Curve



(c) F1 Curve



(d) Precision-Recall Curve

Figure 6.7: Evaluation Curves for YOLO object detector

6.3.1.1.1 Dfl_loss: This metric measures the loss associated with the distance between predicted bounding box coordinates and ground truth bounding box coordinates. It helps in optimizing the model to accurately predict the bounding box locations.

Dfl_loss: 0.9579

6.3.1.1.2 Box_loss: Box loss quantifies the error in predicting the dimensions (width, height) of the bounding boxes. It penalizes the model for inaccuracies in bounding box size prediction.

Box Loss: 0.7546

6.3.1.1.3 Cls_loss: Classification loss is associated with the accuracy of predicting the class labels for the objects detected within the bounding boxes. It penalizes the model for misclassification of objects.

Classification Loss: 0.4153

6.3.1.1.4 Recall: Recall measures the proportion of actual positive samples that were correctly identified by the model. In the context of object detection, it evaluates how well the model can detect all relevant objects in the image.

Recall: 0.617

6.3.1.1.5 Precision: Precision indicates the accuracy of the model's positive predictions. It measures the proportion of correctly predicted positive samples out of all samples that the model has predicted as positive.

Precision: 0.835

6.3.1.1.6 mAP50: Mean Average Precision (MAP) at IoU (Intersection over Union) threshold of 0.5. It evaluates the precision-recall curve for different confidence thresholds and computes the average precision across all classes at an IoU threshold of 0.5.

MAP at 0.5: 0.69

6.3.1.1.7 mAP50-95: Mean Average Precision (MAP) calculated by averaging the precision over different IoU thresholds ranging from 0.5 to 0.95. This metric provides a more comprehensive evaluation of the model's performance across a range of IoU thresholds, capturing both high and low IoU matches between predicted and ground truth bounding boxes.

MAP from 0.5 to 0.95: 0.369

6.3.1.2 Confusion Matrix

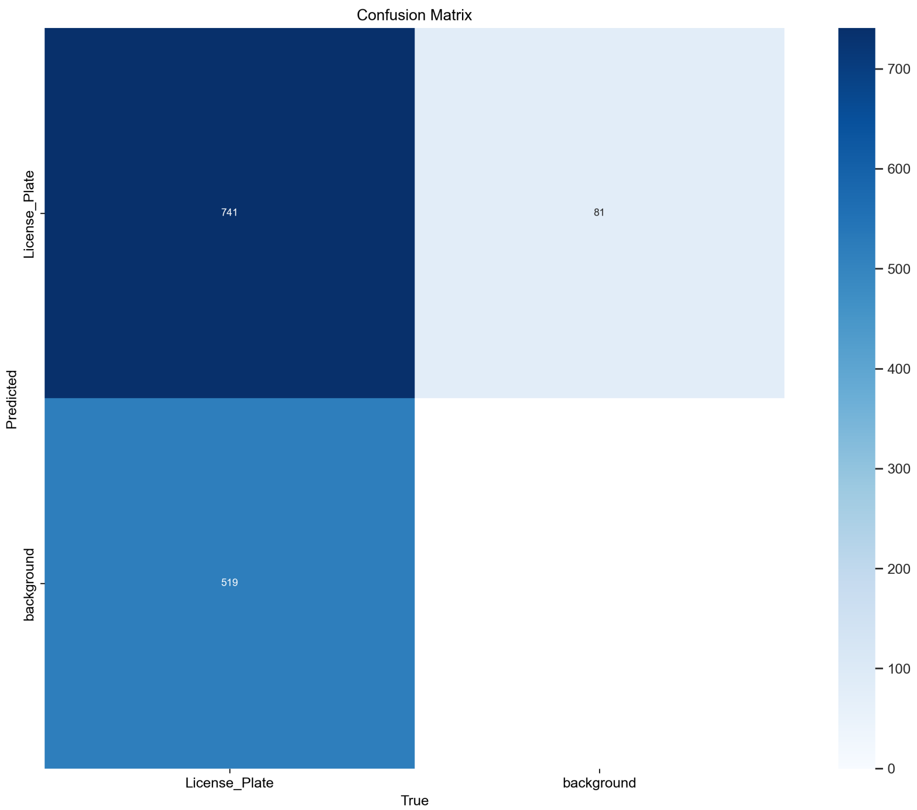


Figure 6.8: Confusion Matrix for YOLO object Detector

6.3.1.3 Flowchart

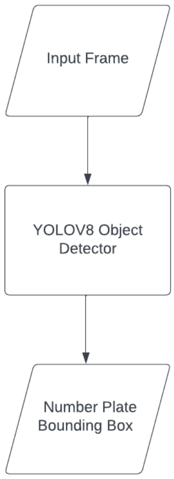


Figure 6.9: Flow chart for Number Plate Localization

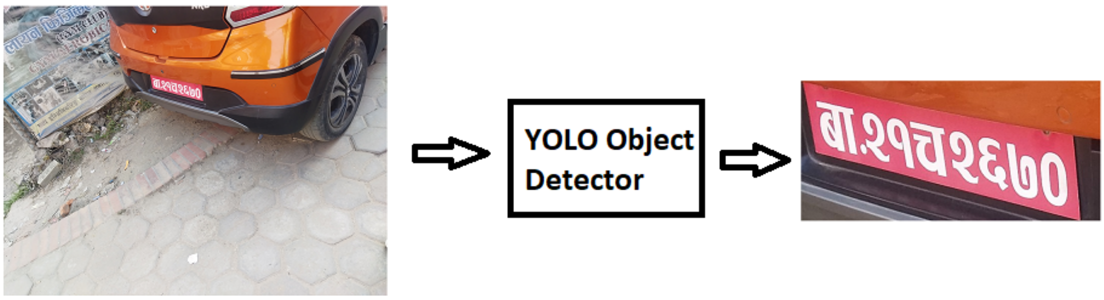


Figure 6.10: Number Plate Localization

6.3.2 Image Alignment

After obtaining the region of interest (ROI) containing the number plate, the image undergoes further preprocessing steps to address skewness, perspective distortion, and remove excess regions beyond the number plate area.

6.3.2.1 Boundary Coordinates Detection

1. Firstly, the edge of the localized image is extracted using canny edge detection [9] algorithm.
2. A boundary-fill [10] algorithm is initiated from the center of the edge-detected image, expanding outward until the boundary is reached.
3. Simultaneously, the algorithm records the boundary coordinates encountered during the boundary-fill process.

Figure 6.11: Localized Number Plate

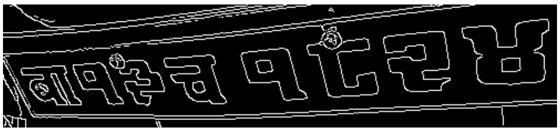


Figure 6.12: Edge Detection

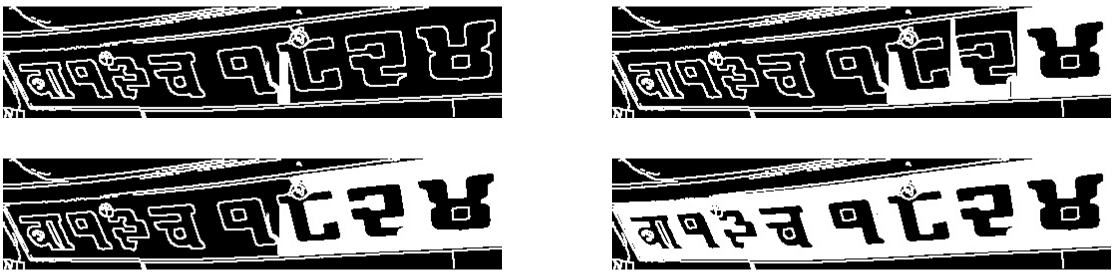


Figure 6.13: BoundaryFill

6.3.2.2 Fitted Hull Convex for Zigzag Removal

1. To mitigate zigzag artifacts resulting from suboptimal edge detection, a fitted hull convex is applied to the recorded boundary coordinates using convexHull function provided by OpenCV [11]. This technique helps to smooth out irregularities in the detected boundaries, resulting in cleaner and more uniform contours.
2. If the center point falls within a character, an area threshold is set for the fitted hull convex. If the area falls below this threshold, the boundary-fill process is restarted from a point adjacent to the previous position.

3. This process continues until the area of the hull convex exceeds the set threshold.

Figure 6.14: Hull Convex

6.3.2.3 Approximation of Corner Points

1. The corner points of the convex hull are approximated using the approxPolyDP function provided by OpenCV. This function simplifies the contour representation by reducing the number of vertices while preserving the essential shape characteristics.

Figure 6.15: Corner Point Detection

6.3.2.4 Perspective Transformation

1. A perspective transformation is applied to the image using the warpPerspective function provided by OpenCV. This transformation maps the corner points of the detected region to a rectangular target area, resulting in a flat representation of the number plate.

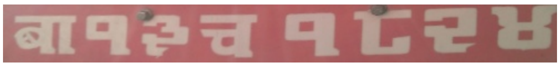


Figure 6.16: Perspective Transformed Image

6.3.2.5 Result

The image alignment process yields a flat, unskewed, and undistorted image containing only the number plate, effectively eliminating excess regions. This refined image serves as ideal input for character segmentation, ensuring precise and accurate identification of alphanumeric characters.

6.3.2.6 Flowchart

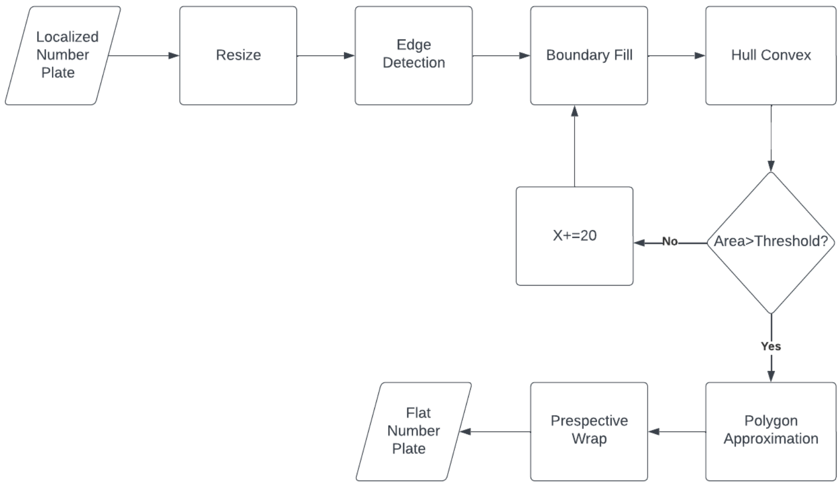


Figure 6.17: Flow Chart for Image Alignment

6.3.3 Character Segmentation

Character segmentation is a pivotal component of the Automatic Number Plate Recognition (ANPR) system, responsible for isolating individual characters from the number plate region. This process is essential for accurate character recognition and subsequent interpretation. Below, we outline the character segmentation methodology employed in our ANPR system.

6.3.3.1 Image Preprocessing

Before character segmentation, the captured number plate region undergoes preprocessing to enhance image quality and facilitate segmentation. The following preprocessing steps are implemented:

1. **Grayscale Conversion**: The captured RGB image is converted to grayscale to simplify processing.
2. **Thresholding**: Otsu's thresholding [12] method is applied to segment the grayscale image into foreground and background regions based on pixel intensity.
3. **Noise Reduction**: Morphological operations, such as erosion, are applied to remove noise and smoothen the image.

Figure 6.18: Binary Image

6.3.3.2 Bounding Box Detection

The bounding box detection algorithm proceeds as follows:

1. **Connected Component Analysis**: Connected component analysis is performed on the preprocessed image to identify distinct regions corresponding to individual characters.
2. **Filtering based on Size**: Components are filtered based on their size to remove noise and retain only regions corresponding to characters. The size threshold is dynamically determined based on the size of the largest connected component.
3. **Contour Detection and Bounding Box Extraction**: Contours of the filtered components are detected, and bounding boxes are computed to encapsulate each character region.
4. **Sorting of Bounding Boxes**: Bounding boxes are sorted based on their x-coordinate to ensure the characters are extracted in the correct sequence.

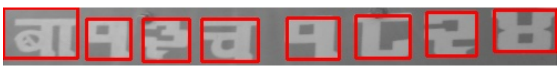


Figure 6.19: Bounding boxes on characters

6.3.3.3 Character Extraction

Once the bounding boxes are obtained, they are used to extract individual character regions from the grayscale image.

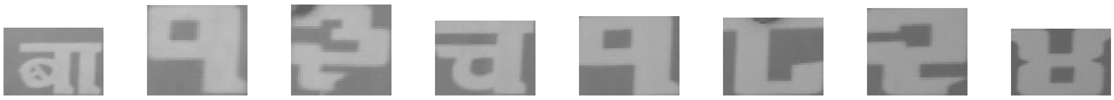


Figure 6.20: Character Extraction

6.3.3.4 Result

The character segmentation process yields segmented character images, which are subsequently fed into the recognition module for alphanumeric character identification. Accurate character segmentation significantly enhances the overall performance and accuracy of the ANPR system.

6.3.3.5 Flowchart

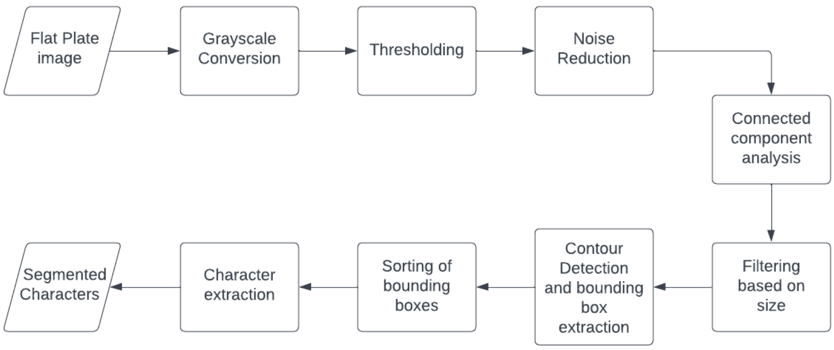


Figure 6.21: Flow chart for Character Segmentation

6.3.4 Character Classification

After segmenting the characters from the number plate images, the next step involves classifying each character into its respective category. This process is essential for accurately recognizing the alphanumeric characters present on the number plate. Below is the procedure followed for character classification:

6.3.4.1 Image Resizing

Each character image is resized to a fixed size of 64x64 pixels. This resizing ensures uniformity in the dimensions of the input images, facilitating consistent feature extraction.

6.3.4.2 Feature Extraction using HOG

Histogram of Oriented Gradients (HOG) [13] features are computed for each resized character image. HOG is a widely used technique for object detection and feature extraction in image processing. It captures the distribution of gradients or edge directions within an image region.

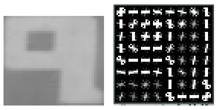


Figure 6.22: HOG Feature Extraction

6.3.4.3 Normalization of Features

The extracted HOG features are flattened into a one-dimensional array and then normalized using a trained scaler. Normalization ensures that the feature values are within a standardized range, enhancing the performance of the classification model.

6.3.4.4 Classification using SVM

The normalized feature vector is fed into a Support Vector Machine (SVM) [14] model for classification. SVM is a supervised learning algorithm commonly used for classification tasks. It works by finding the hyperplane that best separates the different classes in the feature space.

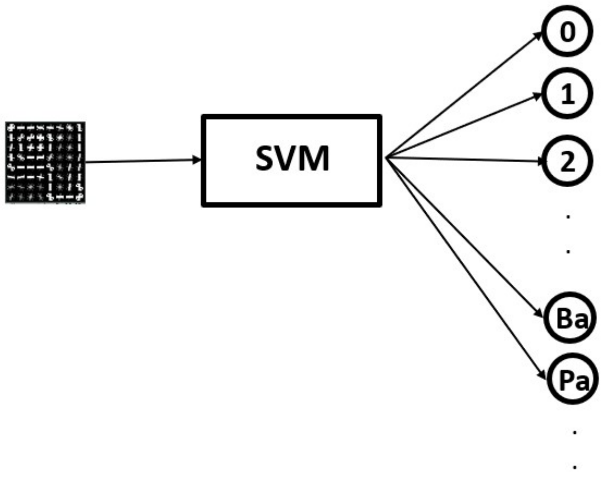


Figure 6.23: Classification using SVM

6.3.4.5 Classification Model Training Metrics

The SVM model used for character classification was trained on the previously mentioned dataset. The following metrics were obtained during the training process:

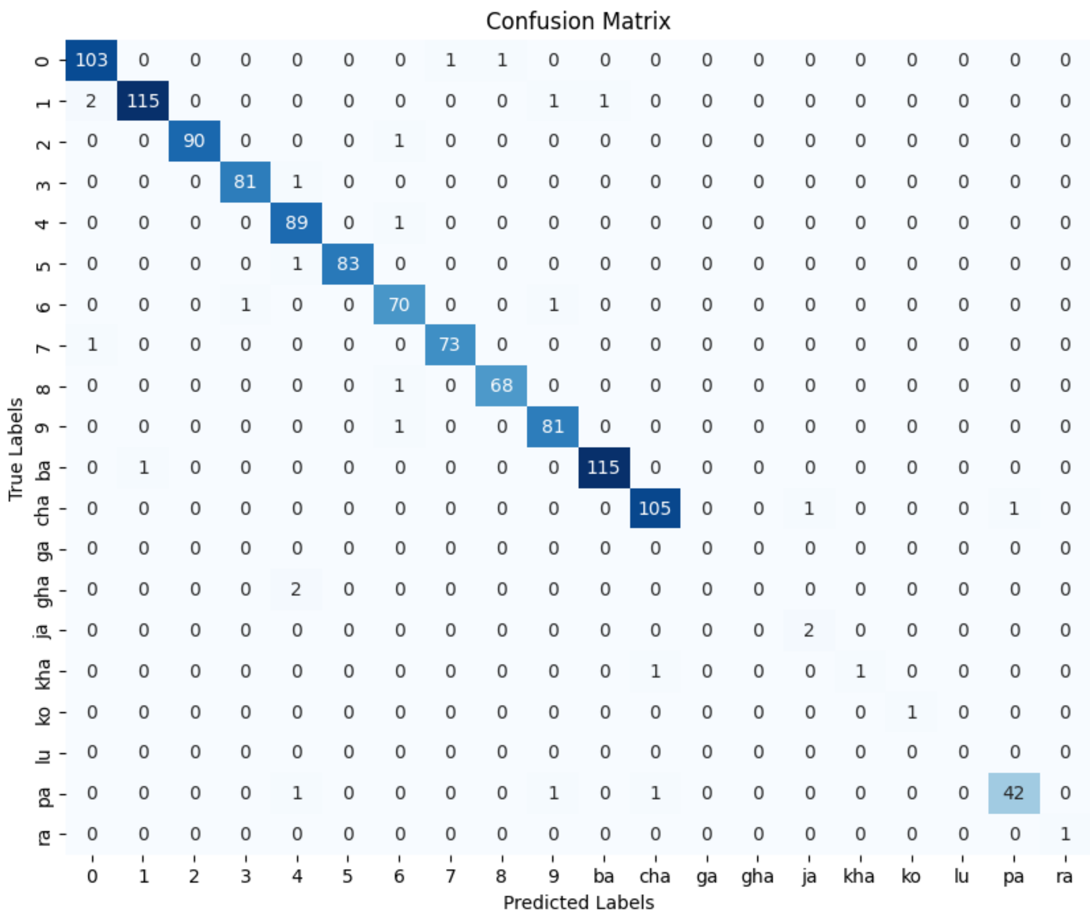


Figure 6.24: Confusion Matrix For SVM

- Accuracy: 0.9839357
- Precision: 0.984179
- Recall: 0.98393587
- F1 Score: 0.983934

These metrics indicate the performance of the SVM model in classifying characters, demonstrating high accuracy, precision, recall, and F1 score.

6.3.4.6 Prediction and Output

The SVM model predicts the class label for the input character based on its extracted features. The predicted label represents the alphanumeric character recognized in the image.

6.3.4.7 Flowchart

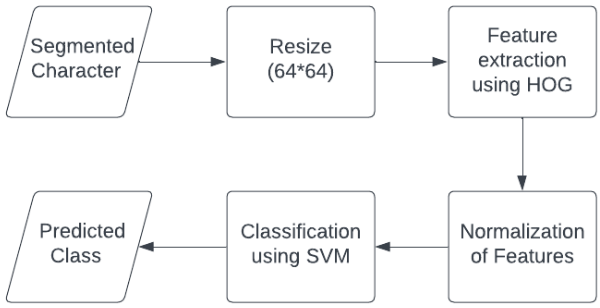


Figure 6.25: Flow Chart for Character Classification

6.4 Overall System Pipeline

The Automatic Number Plate Recognition (ANPR) system encompasses a comprehensive pipeline designed to efficiently process multiple camera feeds, match recognized number plates against a database of demanded plates, and notify authorities of relevant sightings. The pipeline consists of the following key components:

6.4.1 Simultaneous Processing of Camera Feeds

Individual NPR module handle the feed from multiple cameras simultaneously. Each camera captures images in real-time, which are then processed independently to detect and extract number plates using the implemented ANPR algorithms as shown in figure5.3

6.4.2 Database of Demanded Number Plates

The system maintains a database containing records of demanded number plates, which are of interest to law enforcement agencies for various reasons such as tracking suspects or vehicles involved in criminal activities.

6.4.3 Number Plate Recognition and Logging

When a number plate is detected in the camera feed, the system compares it against the database of demanded plates. If a match is found, indicating the presence of a sought-after vehicle, the system logs the hit in the database as shown in figure5.5.

6.4.4 Front-end Polling and Notification

The front-end interface periodically polls the database for new hits logged by the system. This polling occurs at regular intervals, typically every 5 seconds, to ensure timely detection of relevant sightings as shown in figure5.7.

6.4.5 Notification to Authorities

Upon detecting a new hit in the database, the system generates a notification to alert authorities. The notification includes essential details such as:

1. Snapshot: A captured image showing the vehicle with the demanded number plate.
2. Location: The geographical location where the sighting occurred.
3. Timing: The timestamp indicating when the sighting took place.
4. Description: Additional information or metadata associated with the sighting, such as vehicle color or model.
5. Path Tracking: The historical path taken by the suspect vehicle, derived from previous hits stored in the database. This information aids authorities in understanding the movement patterns and behavior of the suspect.

Chapter 7

Result and Discussion

The Automatic Number Plate Recognition (ANPR) system presented in this project offers several advantages and innovations that significantly enhance its effectiveness and applicability in various scenarios. In this discussion, we highlight the advantages of the ANPR system and the impact of incorporating novel techniques, particularly in image alignment, on its accuracy and efficiency.

7.0.1 Advantages of ANPR System

The ANPR system provides numerous benefits, making it a valuable tool for various applications:

1. **Enhanced Traffic Monitoring:** By automating the process of license plate detection and recognition, the ANPR system improves traffic monitoring capabilities, enabling authorities to efficiently manage traffic flow, detect violations, and respond to incidents in real-time.
2. **Improved Law Enforcement:** With the ability to accurately identify vehicles and match them against databases of interest, law enforcement agencies can effectively track and apprehend suspects, locate stolen vehicles, and enforce traffic regulations, contributing to enhanced public safety.
3. **Security and Surveillance:** The ANPR system enhances security and surveillance efforts by enabling the identification and tracking of vehicles entering restricted areas, monitoring parking lots, and identifying suspicious vehicles or activities.
4. **Data Analysis and Insights:** The data collected by the ANPR system can be analyzed to extract valuable insights into traffic patterns, vehicle movements, and compliance with regulations, supporting evidence-based decision-making and urban planning initiatives.

7.0.2 Impact of Image Alignment Technique

The incorporation of advanced image alignment techniques, as demonstrated in this report, has a significant impact on the accuracy and efficiency of the ANPR system:

1. **Improved Accuracy:** The use of novel techniques for image alignment results in more accurate localization and recognition of license plates. This leads to fewer false positives and false negatives, enhancing the overall reliability of the system without compromising speed or computational efficiency.

   The effectiveness of these advancements was assessed through rigorous testing. Two Number Plate Recognition (NPR) modules were developed: one utilizing perspective warp and another without it. These modules were subjected to testing on a dataset comprising 72 random images. The results, illustrated in the figure7.1, demonstrate a significant difference in accuracy between the two approaches, highlighting the efficacy of incorporating perspective warp in image alignment techniques.

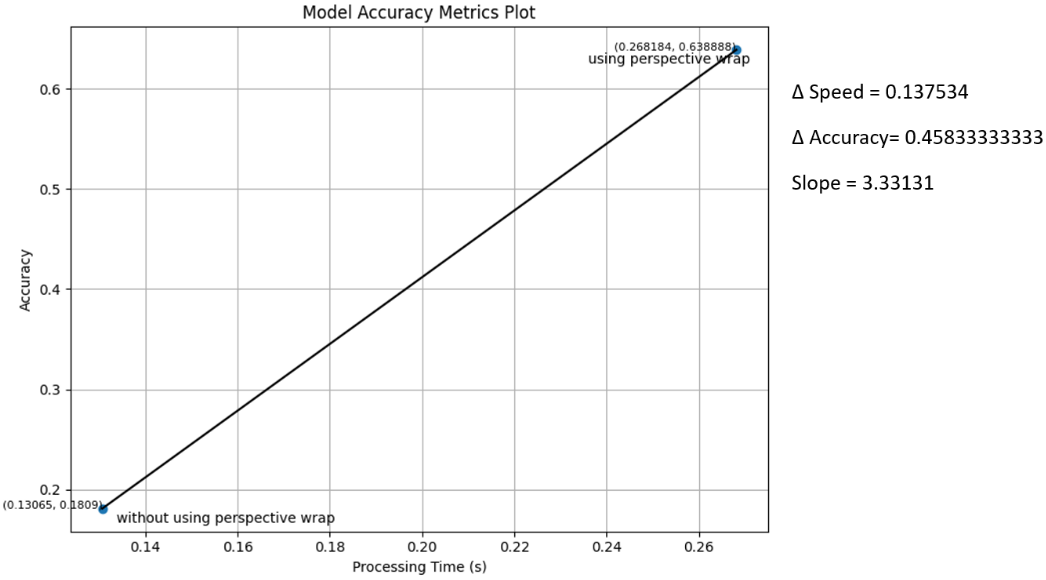


Figure 7.1: Accuracy vs Computational time

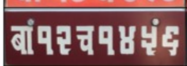
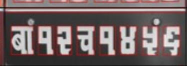
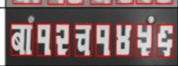
Image	Without Using Perspective Wrap	Prediction	Using Perspective Wrap	Prediction	Actual
		Baba17cha8547 ☒		Ba17cha854 ☑	ba17cha854
		3ba12cha1436 ☒		Ba12cha1436 ☑	ba12cha1436
		1ba13cha3465 ☒		Ba13cha3465 ☑	ba13cha3465
		4428papa3cha ☒		Ba13cha1824 ☑	ba13cha1824
		Baba14cha8914 ☒		Ba14cha891 ☑	ba14cha891
		9ba3cha75931 ☒		Ba3cha7593 ☑	ba3cha7593
		5ba313cha346pa ☒		9ba13cha3465 ☒	ba13cha3465
Accuracy:	0.18055555555		0.63888888888		Ratio = 3.53

Figure 7.2: Outcomes without and with using Perspective wrap

2. **Optimized Camera Deployment:** With the ability to correct distortions in captured images, the ANPR system can achieve accurate results using fewer cameras. This optimization reduces infrastructure costs and simplifies deployment, making the system more scalable and cost-effective.
3. **Increased Flexibility:** By mitigating the effects of environmental factors such as camera angles, image alignment techniques enhance the system's adaptability to diverse operating environments. This flexibility allows the ANPR system to perform reliably in challenging conditions, ensuring consistent performance across different scenarios.
4. **Streamlined Maintenance:** The improved accuracy and robustness of the ANPR system reduce the need for frequent recalibration and maintenance, leading to cost savings and operational efficiencies. Maintenance efforts can be focused on optimizing system performance and addressing specific challenges, rather than addressing recurring issues related to image distortion.

In conclusion, the ANPR system, enhanced by advanced image alignment technique, offers a versatile and reliable solution for various applications in traffic management, law enforcement, and security. By leveraging these advancements, organizations can achieve greater efficiency, effectiveness, and insight in their operations, ultimately contributing to safer and smarter urban environments.

Chapter 8

Conclusion and Future Enhancements

8.1 Conclusion

In conclusion, our Automatic Number Plate Recognition (ANPR) project, employing YOLOv8 for object detection and Support Vector Machine (SVM) for character recognition, has been effectively developed and deployed as a web-based application. Leveraging YOLOv8 facilitates efficient and real-time license plate detection across diverse scenarios, ensuring reliable performance under varying conditions. Complemented by SVM, our system achieves high accuracy in character recognition, enabling precise interpretation of alphanumeric characters on number plates.

8.2 Future Enhancements

The Automatic Number Plate Recognition (ANPR) system implemented using YOLOv8 for object detection and Support Vector Machine (SVM) for character recognition has shown promising results but can be further improved through future enhancements. Some potential enhancements to consider include:

1. **Utilizing a more advanced object detection model**: YOLOv8, while efficient, may struggle with detecting smaller license plates. Consider exploring newer and more robust object detection models that are better suited for accurately detecting license plates of varying sizes and orientations.
2. **Diversifying the training dataset**: Currently, the system is trained primarily on private vehicle red plates due to dataset limitations. Expanding the training dataset to include a wider range of license plate types (e.g., public vehicles, tourist vehicles) and variations (e.g., different fonts, colors) can improve the system's ability to accurately recognize diverse license plates.
3. **Enhancing character recognition capabilities**: SVM classification is limited by the available dataset, resulting in incomplete classification of alphanumeric characters. Currently, SVM can recognize only the following characters: ba, cha, ga, gha, ja, kha, ko, lu, pa, and ra. To address this limitation, collecting and preparing a more comprehensive dataset covering all possible alphanumeric characters, as well as variations in font styles and sizes, would improve the SVM's ability to accurately classify characters and enhance overall recognition accuracy.

4. **Incorporating embossed number plates**: Currently, the system is not trained for detecting embossed number plates. To address this limitation, future enhancements should include developing algorithms capable of identifying and accurately recognizing embossed number plates, thereby expanding the system's applicability to a wider range of plate types.

5. **Adaptation for new number plate formats**: With the introduction of new number plate formats featuring province-wise identification, it becomes essential to adapt the ANPR system to recognize and interpret these variations. This involves updating the system's algorithms and training data to accommodate the new formats, ensuring reliable recognition and compliance with evolving standards in license plate design.

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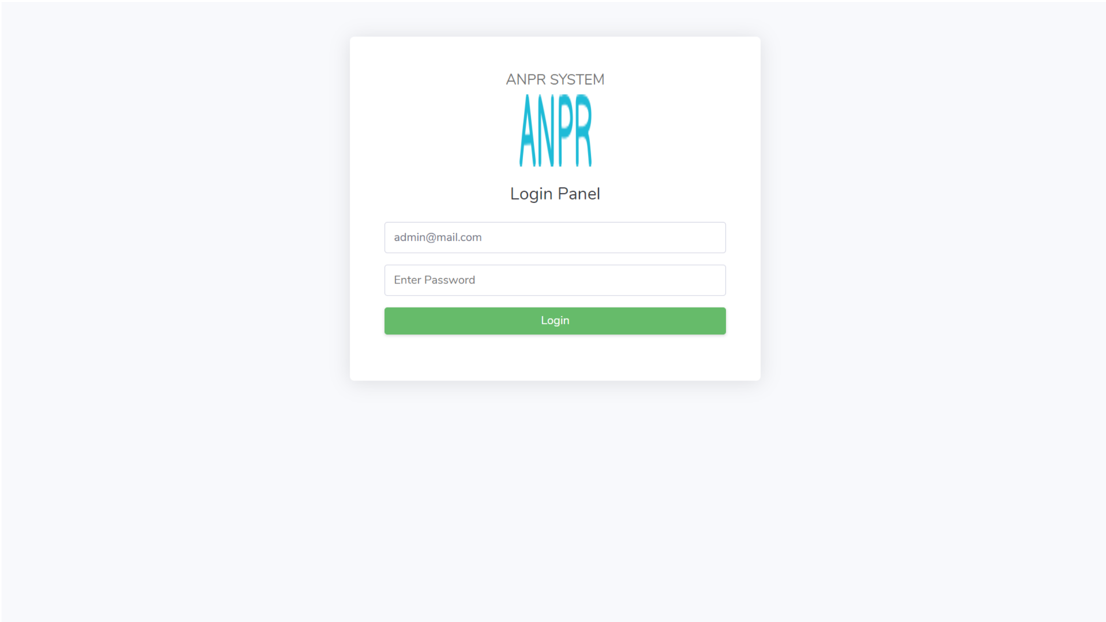
Chapter 9

Appendix

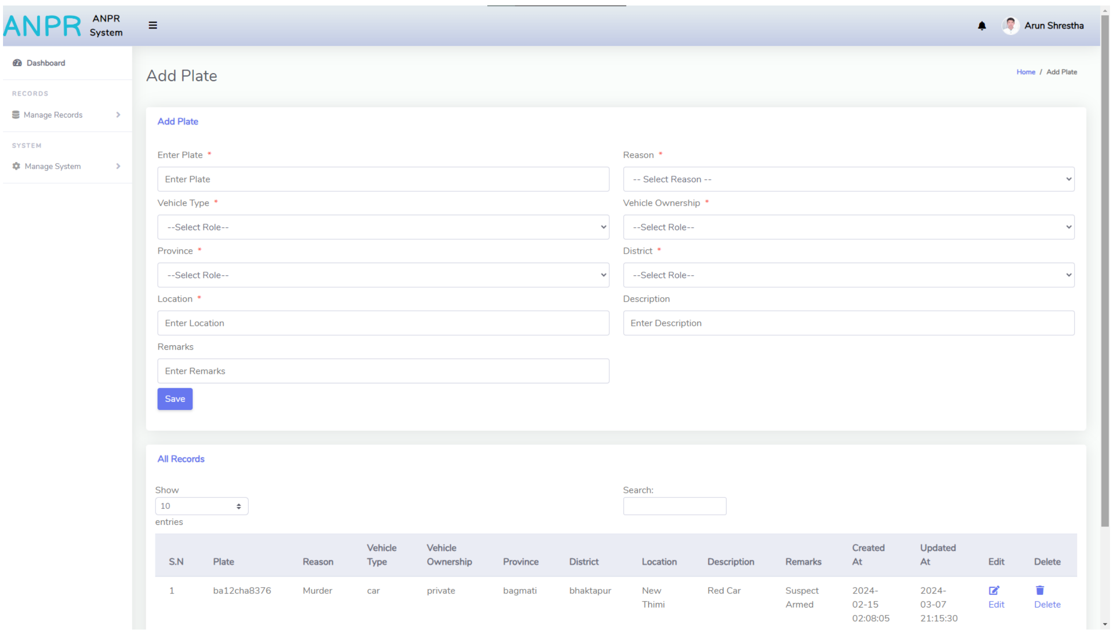
A Snapshots

A.1 Login

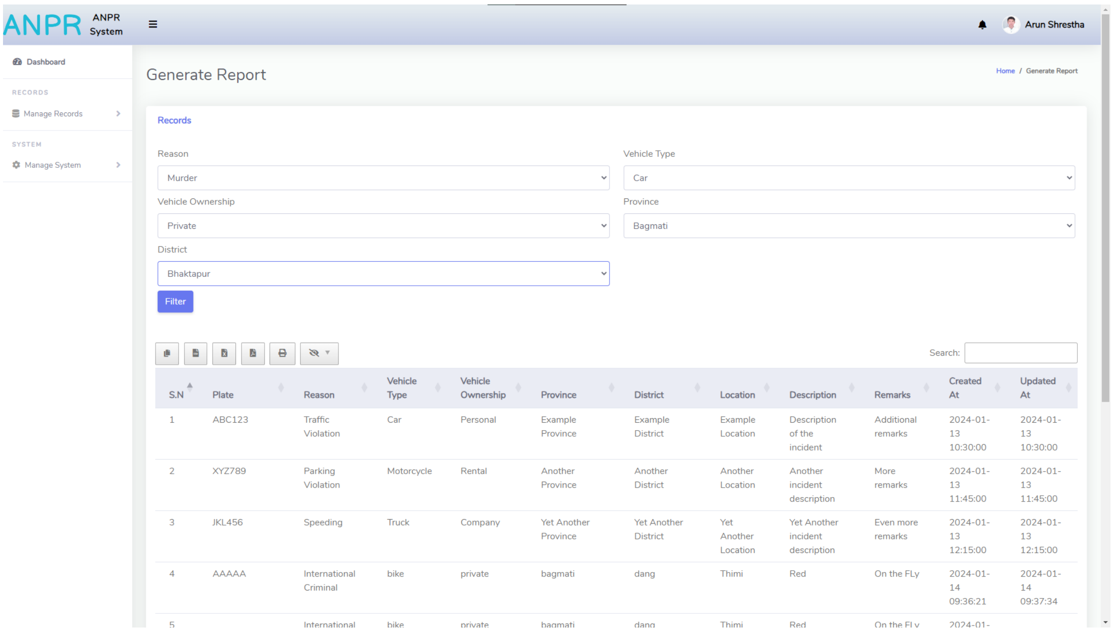


A.2 Dashboard

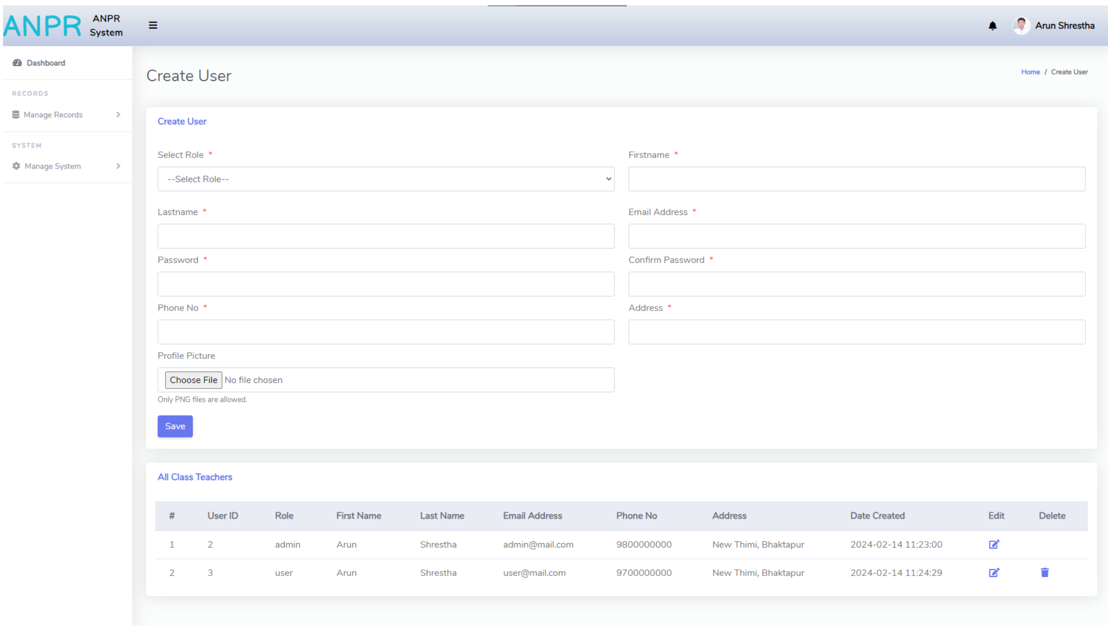
A.3 Create Records



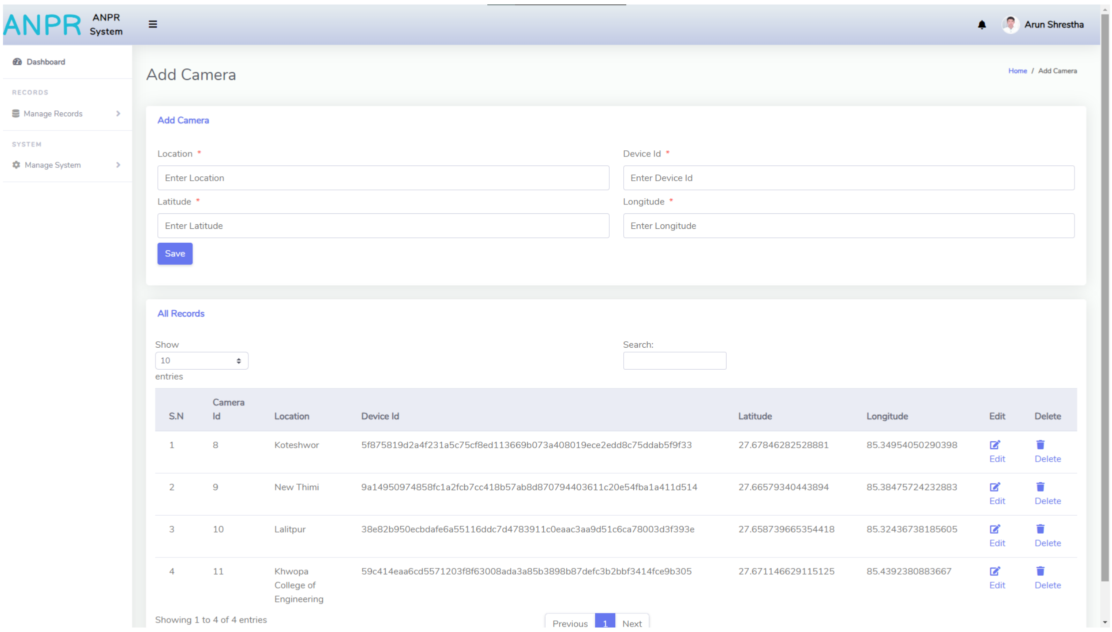
A.4 Generate Report



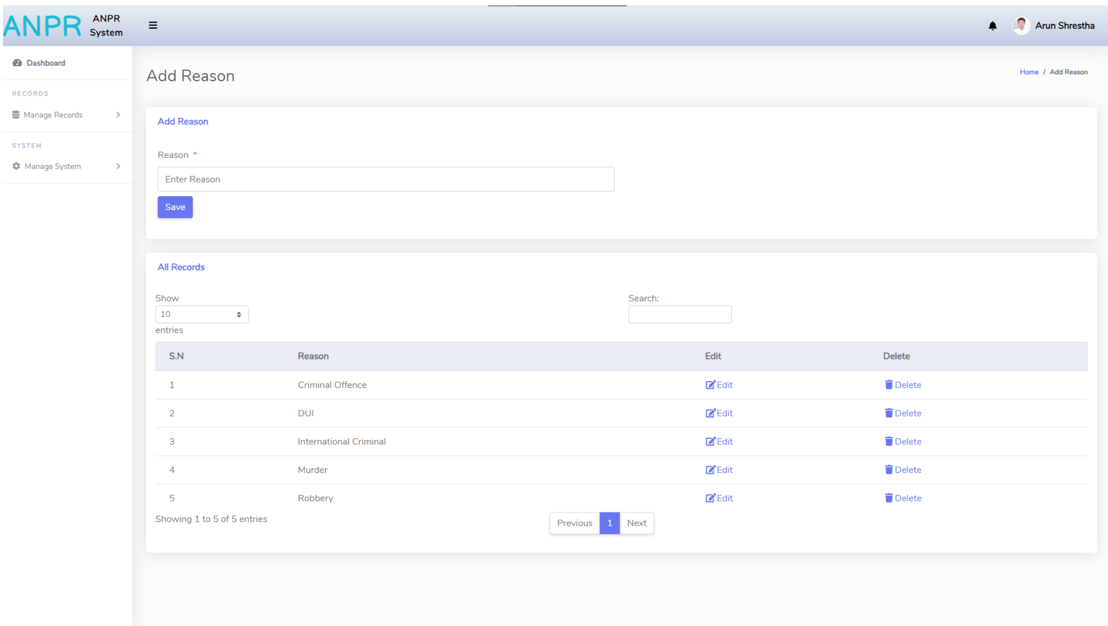
A.5 Manage Users



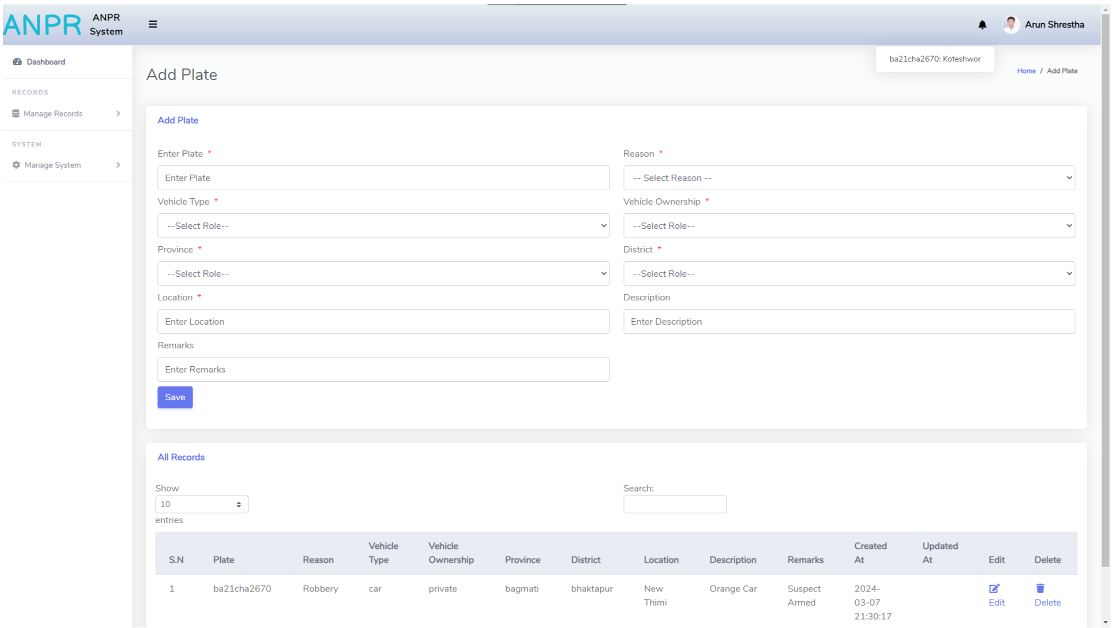
A.6 Manage Camera



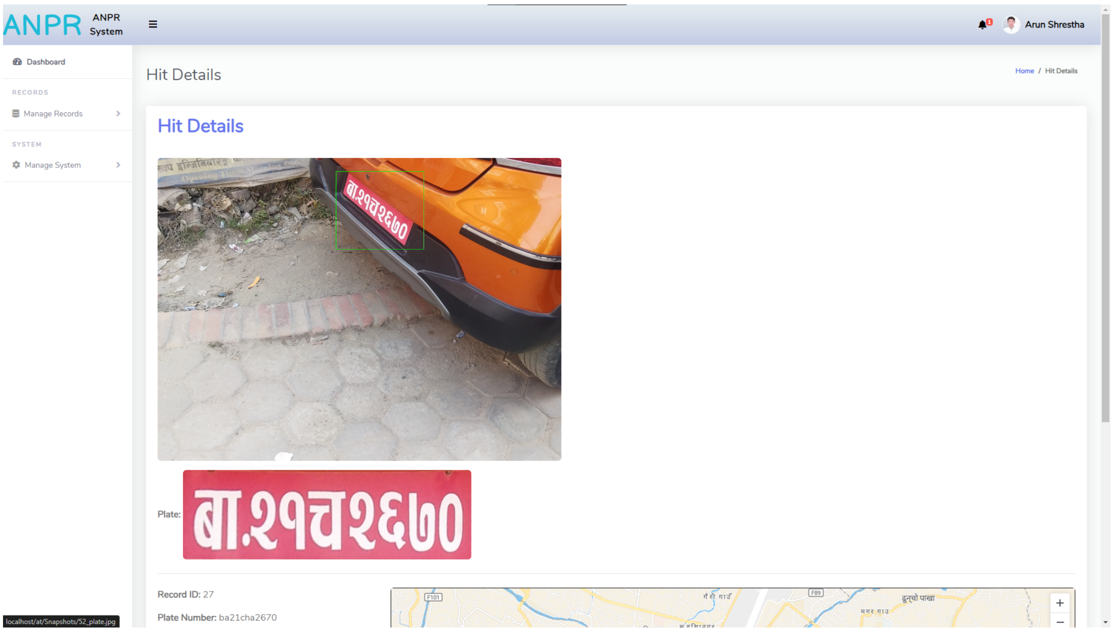
A.7 Manage Reason



A.8 Notification



A.9 Hit Details



A.10 Hit Location