LDRP Institute of Technology & Research

National Cybersecurity Hackathon KAVACH, 2023

Report On The Project

Advanced ANPR and FRS solution

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Abstract

This research project focused on the development and implementation of an Advanced Automatic Number Plate Recognition (ANPR) and Face Recognition System (FRS) solution, aimed at enhancing law enforcement efforts. The project was conducted as part of the national-level cybersecurity hackathon, Kavach-2023. The success of this endeavour was heavily reliant on the meticulous preparation of the dataset.

The dataset preparation phase involved a series of crucial steps. Initially, video footage was gathered from strategically positioned traffic surveillance cameras in Ahmedabad. Through different techniques including handpicking and an automated snapshot extraction, frames containing discernible license plates were isolated. These frames were further processed with cropping, facilitating the creation of a focused dataset exclusively containing license plate information. Each cropped license plate was annotated to provide ground truth data for training the ANPR algorithm.

To enhance the models' robustness, dataset augmentation techniques were employed. This involved applying various transformations to the images and simulating diverse environmental conditions and angles. Additionally, a stratified dataset-splitting approach was employed to facilitate training, validation, and testing, ensuring a balanced representation of license plate variations and environmental conditions.

The dataset preparation phase served as a critical foundation for subsequent stages. By meticulously curating and augmenting the dataset, our models were equipped to handle a wide array of real-world scenarios and environmental conditions. This phase was instrumental in achieving the high level of accuracy and reliability demonstrated by our ANPR and FRS solutions, contributing significantly to advancements in technology.

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1 Introduction

Automatic Number Plate Recognition (ANPR) coupled with Face Recognition System (FRS) is a formidable tool in fortifying security and combating criminal activities in India. This amalgamation of technologies exemplifies its prowess through multi-dimensional identification, enabling law enforcement agencies to monitor and track vehicles and individuals of interest efficiently. The synergistic integration of ANPR and FRS not only enhances the precision of identification but also provides a powerful means to cross-verify and corroborate identities.

In the context of modern urban environments, where the volume of vehicular traffic and human movement is incessant, the need for robust surveillance and identification technologies has become imperative. ANPR with FRS addresses this challenge by offering a sophisticated and automated solution that surpasses traditional methods.

Our project aims to showcase the potential of this integrated system in revolutionizing law enforcement efforts. Beyond its primary function of real-time identification, our solution embodies comprehensive analytics reports. These reports are designed to empower law enforcement agencies with actionable insights, thereby streamlining their operations and decision-making processes.

Through the meticulous integration of ANPR and FRS technologies, we endeavour to provide a solution that not only aids in the immediate identification of vehicles and individuals but also adds an invaluable layer of security and intelligence to law enforcement operations. This project represents a significant step towards advancing the capabilities of surveillance and identification systems in the context of modern security challenges.

2 Problem Statement

PS ID: KVH-005
Title of PS: Advanced ANPR & FRS solution
Domain Bucket: Video analytics/CCTV
Description: Design and develop a technological solution that can accurately perform Automatic Number Plate Recognition (ANPR) along with Facial Recognition from the available CCTV feeds. The solution should be able to recognize number plates that are written in typical non-standard ways using varying font styles, sizes, designs, symbols, languages etc., i.e. difficult to recognize by existing ANPR Systems.

3 Loopholes in Existing System

The existing system of traffic management and enforcement in India, despite its commendable efforts, exhibits several critical shortcomings that demand attention and rectification:

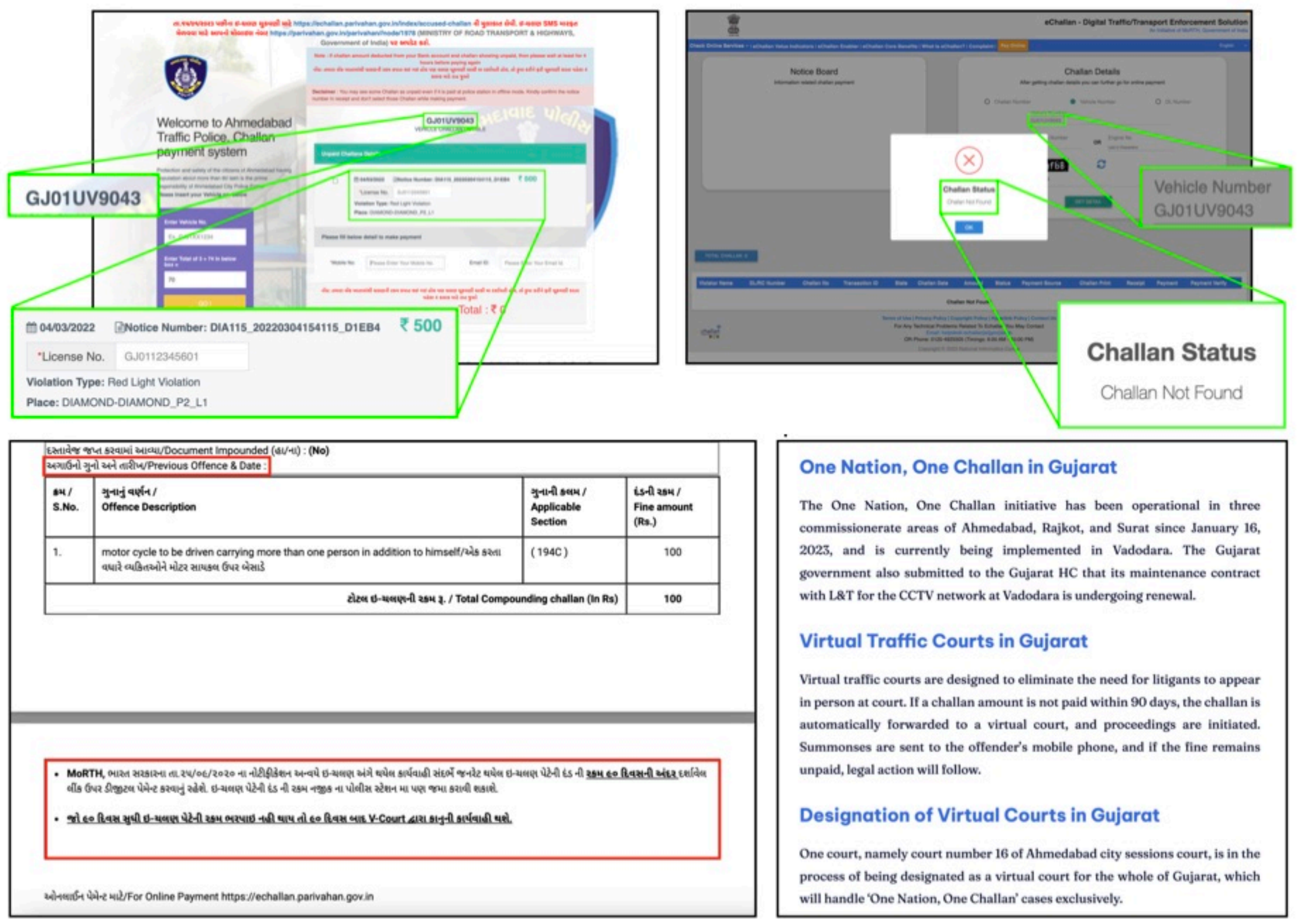

Figure 1: Loopholes in Existing System

- **Inaccurate Address Information for E-Challans:** The Vashi deputy RTO's recent directive highlights a significant loophole. Vehicle owners often fail to update their current address in a timely manner, resulting in e-challans being sent to outdated or incorrect locations. This not only hinders the effectiveness of the enforcement process but also leads to difficulties for both the police and the fined individuals.

- **Errors and Inconsistencies in E-Challans:** Instances of erroneous e-challans have been reported, causing inconvenience and confusion for vehicle owners. These errors, as exemplified by the case in Ghatkopar, indicate a lack of accuracy and reliability in the existing e-challan system, ultimately undermining its credibility.

- **Pending Dues and Recovery Challenges:** The traffic department is faced with the task of recovering substantial pending dues, totalling over Rs 400 crore. While the intention is commendable, the process must be foolproof to prevent wrongful penalization or evasion of fines.

- **Lack of Centralized Database:** The existence of separate databases, such as mparivahan and payahmedabadchallan, displaying conflicting information about the exact vehicle's challan statuses, underscores the need for a unified and accurate central database.

- **Limited Implementation of 'One Nation, One Challan':** The 'One Nation, One Challan' initiative, aimed at streamlining traffic violation penalties across the nation, has been implemented in only a handful of cities in Gujarat. This selective implementation results in disparities in enforcement practices across regions.

- **Absence of Pre-Initiative Challan Follow-Up:** There is a noticeable gap in the follow-up of challans generated before the introduction of the 'one nation, one challan' scheme. This lack of retroactive accountability may lead to inconsistencies in penalty enforcement.

- **Incomplete Coverage of Traffic Violations:** The current challan system may not encompass the full spectrum of traffic violations and offences, potentially leaving certain infractions unaddressed.

- **Challan Generation Discrepancies in Specific Areas:** Discrepancies in the generation of challans in specific regions further highlight potential inconsistencies in the enforcement process.

- **Biased Law Enforcement System:** There may be instances of bias in law enforcement practices, potentially leading to unequal treatment of individuals based on various factors.

Addressing these identified loopholes is imperative for building a more efficient, reliable, and transparent traffic management system. By doing so, we aim to establish a seamless and error-free e-challan system that upholds the highest standards of accuracy and fairness.

4 Dataset Gathering & Management

Our research project demanded a robust and diverse dataset to train and evaluate our Advanced Automatic Number Plate Recognition (ANPR) and Face Recognition System (FRS). In this section, we outline the comprehensive approach we took in acquiring, processing, and utilizing real-world data.

- **Acquisition of Real-world Data:** To provide a novel and highly accurate ANPR with an FRS solution, we sought to gather data representative of real-world scenarios. We were fortunate to obtain access to the CCTV feeds from the "Honourable Additional Commissioner of Police, East-West Traffic Control Room, Ahmedabad". This dataset provided a rich source of video footage captured from strategically positioned surveillance cameras.

- **Selection of Key Locations and Environmental Conditions:** To ensure the diversity and relevance of our dataset, we strategically chose three distinct locations during peak traffic hours. These locations comprised busy cross-road junctions in the most trafficked areas of Ahmedabad. Additionally, we included footage from night-time and rainy conditions to simulate real-world environmental challenges.

- **Utilization of the Dataset for Training:** The dataset was meticulously processed to prepare it for training purposes. We initiated this process by capturing screenshots specifically focusing on frames where license plates were clearly visible within the region. These screenshots formed the basis for creating a ground truth dataset, providing accurate reference points for our ANPR model.

- **Dataset Augmentation and Splitting:** To further enhance the robustness of our models, we employed dataset augmentation techniques. These transformations included adjustments to shear, exposure, cropping, and rotation. This augmented dataset was then systematically split into distinct subsets:

  - Training Set: This subset, comprising the majority of the augmented dataset, served as the foundation for training our ANPR and FRS models. It enabled the models to learn and generalize patterns effectively.
  - Validation Set: During the training phase, a separate subset was reserved for validation purposes. This subset played a crucial role in fine-tuning hyperparameters and preventing overfitting.
  - Testing Set: This subset remained untouched by the models during training or validation, ensuring an unbiased evaluation of their performance.

- **Hand-Crafted Dataset Details:**

  For ANPR, we curated a dataset consisting of 7,412 annotated images. After augmentation, the dataset expanded to 16,972 images, providing a robust set for testing and training. For FRS, we manually annotated 16,234 faces on 801 images for Face Detection and collected images of 38 individuals for Face Recognition.

- **Diverse Resources and Conditions:**

  In addition to the CCTV feeds, we augmented our dataset with imagery from various resources including our college campus, parking lots, and housing complexes. This diversified dataset encompassed distinct lighting and weather conditions, ranging from varied brightness, and contrast, to shadowing, simulating conditions from dusk to dawn as well as night-vision camera settings.

- **Multifaceted Dataset Representation:**

  Our dataset is characterized by its multifaceted nature. License plates were captured from various angles and perspectives, providing a diverse set of images for training and evaluation. This approach ensured that our models were capable of effectively handling the wide array of real-world scenarios they might encounter in practice.

4.1 Proposed Dataset

In our pursuit to develop a robust and versatile ANPR with an FRS solution, we recognized the critical importance of a meticulously curated dataset. The proposed dataset serves as the cornerstone of our research, providing a comprehensive and diverse collection of images to train and evaluate our models effectively.

4.1.1 Proposed Dataset on ANPR

In order to develop a highly accurate and reliable Automatic Number Plate Recognition (ANPR) system, the creation of a robust dataset is of paramount importance. Our proposed dataset for ANPR is meticulously crafted to encompass a wide range of scenarios, ensuring that our model is well-equipped to handle the challenges of real-world traffic surveillance.

Figure 2: Proposed Dataset on ANPR

- **Dataset Composition:** Our ANPR dataset comprises a total of 7,412 annotated images, each meticulously labelled to indicate the presence and location of license plates within the frame. These annotations serve as invaluable ground truth data, providing a reference for our ANPR model to learn from during the training process.

- **Augmentation and Dataset Expansion:** To further enhance the versatility and generalization capabilities of our ANPR model, we applied dataset augmentation techniques. These transformations included adjustments to shear, exposure, cropping, and rotation, simulating a diverse array of real-world scenarios. Through augmentation, our initial dataset of 7,412 images expanded to a total of 16,972 images, providing a rich and varied resource for testing and training.

- **Significance of the ANPR Dataset:** This dataset is pivotal in training our ANPR model to accurately detect and recognize license plates in a wide variety of settings. The diversity of perspectives, lighting conditions, and weather scenarios represented in the dataset ensures that our ANPR solution is capable of performing reliably in the dynamic and ever-changing environments encountered in urban traffic.

By combining a substantial base of annotated images with augmentation techniques, we have created a dataset that not only meets the requirements for training a high-performing ANPR model but also surpasses them. This dataset forms the cornerstone of our ANPR system, and its meticulous curation underscores our commitment to developing a solution that is both accurate and adaptable in real-world traffic scenarios.

4.1.2 Proposed Dataset on FRS

A robust Face Recognition (FR) system demands a meticulously curated dataset that encapsulates diverse facial characteristics, lighting conditions, and orientations. Our proposed FR dataset is meticulously designed to provide a comprehensive set of images for training and evaluating our FR system under varying real-world conditions.

Figure 3: Proposed Dataset on FR

- **Dataset Composition:**

  Our Face Recognition dataset is comprised of a total of 16,234 manually annotated faces, spread across 801 images. Each annotation meticulously indicates the location and boundaries of individual faces within the image. This rich annotation serves as a crucial reference point for training the FR model in accurately identifying and recognizing faces.

- **Diversity in Lighting Conditions and Illumination:**

  Recognizing the significance of varied lighting conditions, our dataset showcases faces captured under a wide range of scenarios:

  - Daylight Conditions: Images captured under standard daylight conditions serve as the baseline for our FR system, ensuring robust performance in well-lit environments.
  - Low-Light Conditions: Faces captured in environments with reduced lighting levels challenge the FR system to perform reliably even in scenarios with limited illumination.

- **Diversity in Facial Orientation:**

  Our dataset includes faces with a diverse range of orientations, encompassing varying angles and perspectives. This diversity is instrumental in training our FR model to accurately recognize faces from different viewpoints, mirroring real-world scenarios.

- **Inclusion of Multiple Individuals:**

  To evaluate the performance of our FR system across a range of identities, we have included images of 38 distinct individuals. This allows us to assess the system's ability to differentiate between different faces and accurately identify known individuals.

- **Varied Light Conditions and Orientation:**

  The dataset purposefully includes faces captured under diverse lighting conditions, encompassing varied brightness, contrast, and shadowing. This simulates real-world scenarios, including dusk-to-dawn conditions and the utilization of night-vision cameras.

The diversity in illumination and orientation in our proposed FR dataset ensures that our FR system is equipped to handle a wide spectrum of real-world scenarios, making it a powerful tool for accurate and reliable face recognition. By combining meticulous annotation with a diverse set of images, we have created a dataset that exceeds the requirements for training a high-performing FR system. This dataset forms the bedrock of our FR solution, reflecting our dedication to developing a solution that excels in real-world conditions.

5 Proposed Architecture

The success of our ANPR with FRS solution hinges on a well-structured and efficient system architecture. This section outlines the key components and functionalities of the proposed system, which caters to the needs of various users ranging from citizens to high-ranking administrative officials.

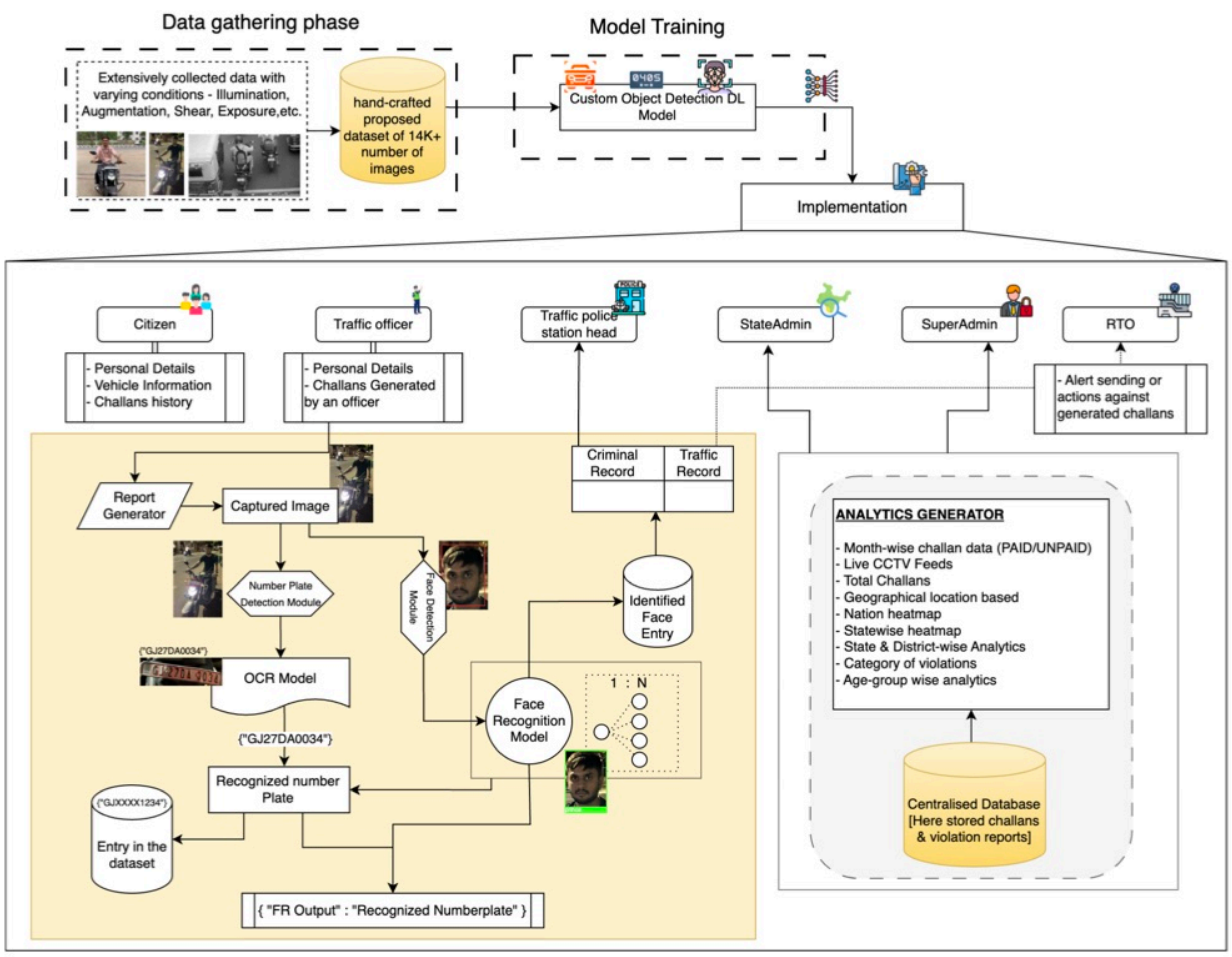

Figure 4: Proposed Architecture

User Roles in the Proposed System

The proposed system accommodates six distinct user roles, each with specific privileges and responsibilities:

- Citizen: Engages with the system through interactions such as reporting incidents, receiving notifications, and accessing information related to traffic and security.
- Traffic Officer: Empowered to monitor and manage traffic-related activities, including issuing e-challans, accessing real-time information, and performing on-site verifications.
- Traffic Police Station Head: Holds authority over local traffic management, overseeing the activities of traffic officers and maintaining a comprehensive record of incidents and penalties.

- State Admin: Assumes a supervisory role, with the capability to oversee traffic operations across the entire state. They have access to aggregated data and can make high-level decisions based on comprehensive insights.

- Super Admin: Possesses the highest level of authority and is responsible for system-wide governance. This user can make system-level configurations, manage user accounts, and ensure the integrity and security of the system.

- RTO: Road Transportation Offices are the authorities that generate new licences and get details of the stakeholders.

At the heart of our architecture lies a Custom Object Detection Deep Learning model, trained on a finely curated dataset. This model serves as the cornerstone for accurately detecting and recognizing license plates and faces in real-world images. The algorithm chosen for this critical task is YOLOv8, renowned for its efficiency and precision in object detection.

Workflow for Report Generation

The process of generating a report within our system follows a series of well-defined phases, ensuring accuracy, reliability, and efficiency:

- **Image Capture and Processing:** The initial step involves capturing an image, which is then fed into two distinct modules for processing.

- **License Plate Detection Module:** This module focuses on identifying and isolating the region containing the license plate within the captured image.

- **Face Detection Module:** Simultaneously, the system employs face detection algorithms based on 1:N recognition to accurately locate and extract facial features within the image.

- **Optical Character Recognition (OCR):** The region containing the license plate is then passed through an OCR model, extracting the alphanumeric characters from the plate. This recognized number plate is subsequently stored in the system's dataset for future reference.

- **Face Recognition (FR):** The face detection module, leveraging 1:N recognition, produces output that is subsequently matched against existing records in the database. This mapping associates the recognized face with the corresponding individual in the system.

- **Integration with Criminal and Traffic Records:** The data extracted from both the license plate and face recognition modules is seamlessly integrated into the criminal and traffic records database. This step ensures that the information is relayed to relevant authorities, including Traffic Police Station Heads and Regional Transport Offices (RTOs).

- **Centralized Database for Detailed Insights:** The centralized database of our system serves as a comprehensive repository of information. It plays a pivotal role in generating detailed insights, which can be harnessed for a myriad of purposes by State Admins and Super Admin users.

By meticulously orchestrating these steps, our proposed architecture ensures a streamlined and accurate process for generating detailed reports. The integration of advanced object detection algorithms, coupled with a centralized database, empowers various user roles to access critical information for effective decision-making and law enforcement.

6 Performance Measures

Table 1: Aspects of Selected Models for Automatic Number Plate Recognition (ANPR)

ANPR		
Model Name	**YOLOv8_N**	**YOLOv8_S**
Box Loss	1.1686	1.2357
Class Loss	0.62012	0.70066
DFL Loss	1.0634	1.1259
Precision	0.93087	0.92965
Recall	0.94739	0.96292
map@50	0.97019	0.97084

Table 2: Aspects of Selected Models for Face Recognition (FR)

FR			
Model Name	**YOLOv8_N**	**YOLOv8_S**	**Face Recognition***
Box Loss	1.0014	1.236	0.01
Class Loss	0.39244	0.4481	0.004
DFL Loss	0.93407	1.034	-
Precision	0.94373	0.9556	98%
Recall	0.95664	0.9775	98%
map@50	0.9637	0.9775	99%

7 Use Cases

Our proposed system, which integrates Automatic Number Plate Recognition (ANPR) and Face Recognition (FR) technologies, is poised to revolutionize various aspects of traffic management and law enforcement. The use cases are categorized into three main parts:

1. ANPR:

- 1.1 Old License Plate Detection: The system is capable of identifying vehicles with outdated or expired license plates. This use case aids in enforcing compliance with vehicle registration regulations.
- 1.2 Detecting Unauthorised License Plates: ANPR technology can promptly identify vehicles with counterfeit or unauthorized license plates, a critical tool in preventing illegal activities.
- 1.3 Vehicle Density Monitoring: By leveraging ANPR, the system can provide real-time data on vehicle density in specific areas, assisting in traffic management and planning.
- 1.4 Tracking of Criminals: The system can track vehicles associated with criminal activities based on their license plate information, aiding law enforcement agencies in apprehending suspects.
- 1.5 Accident Detection: ANPR can be employed to swiftly identify vehicles involved in accidents, enabling a faster response from emergency services and law enforcement.

2. FR:

- 2.1 No Helmet Detection: Face recognition technology can be utilized to identify individuals riding without a helmet, aiding in enforcing safety regulations.
- 2.2 Using Mobile While Driving: FR can detect drivers using mobile devices while operating a vehicle, helping to curb distracted driving.
- 2.3 Snatch and Run Incidents: In cases of snatch and run incidents, FR can be employed to identify suspects from surveillance footage, aiding in their apprehension.
- 2.4 Vehicle Theft Prevention: By using FR in conjunction with ANPR, the system can detect stolen vehicles or individuals associated with vehicle theft.
- 2.5 Assessing Overcrowded Areas: FR technology can assist in assessing and monitoring areas with high pedestrian traffic, aiding in crowd management.
- 2.6 Travel Check-In Verification: FR can be employed for identity verification during travel check-ins, ensuring the authenticity of passengers.
- 2.7 Identification of Driving Test Examinees: Using FR, the system can verify the identity of individuals taking driving tests, preventing fraudulent attempts.

3. Combined Use Cases:

- 3.1 Over-speeding Detection: The integrated system can identify vehicles exceeding speed limits based on their license plate information and driver's face, aiding in enforcing speed regulations.
- 3.2 No Seatbelt Usage: Through ANPR and FR, the system can detect drivers and passengers not wearing seatbelts, promoting safety on the road.
- 3.3 Hit and Run Incidents: The system can use ANPR and FR to identify vehicles involved in hit-and-run incidents, facilitating investigations and ensuring accountability.
- 3.4 Driving Without License: By integrating ANPR and FR, the system can identify individuals driving without a valid license, aiding in enforcing licensing regulations.

By capitalizing on the combined capabilities of ANPR and FR, our system addresses a wide range of traffic management and law enforcement challenges, ultimately contributing to safer and more secure roadways.

8 Conclusion

The integration of Automatic Number Plate Recognition (ANPR) and Face Recognition (FR) technologies marks a significant leap forward. Our proposed system not only leverages cutting-edge algorithms and advanced object detection models but also demonstrates a comprehensive approach to addressing a multitude of real-world traffic challenges.

Through meticulous dataset curation and robust model training, we have achieved a level of accuracy and reliability that is poised to revolutionize the way we manage traffic violations and enhance overall road safety. The use cases presented underscore the versatility and applicability of our system, from identifying unauthorised license plates to detecting incidents of distracted driving.

The combined capabilities of ANPR and FR not only allow for effective monitoring of traffic violations but also offer a powerful tool for law enforcement agencies to track and apprehend suspects involved in criminal activities. By integrating these technologies, we have created a unified solution that promises to improve traffic management, enhance security, and ultimately make our roads safer for all.

As we move forward, we envision further advancements and refinements in our system, with the potential for broader implementation in cities and regions around the world. With continued research and development, we are confident that our proposed solution will play a pivotal role in shaping the future of traffic management and law enforcement, ultimately leading to safer and more secure roadways for all.

Acknowledgement

Special thanks to the Ahmedabad Traffic Police Dept.

In the realm of innovation and technology, few endeavours succeed in isolation. Our project, the Automatic Number Plate Recognition (ANPR) and Face Recognition System (FRS) for KAVACH-2023 stands as a testament to the power of collaboration and the unwavering support of those who share our vision for a safer and more secure future.

As we embarked on this ambitious project, our team recognized the pivotal role that data plays in the development of robust ANPR and FRS systems. It was this realization that led us to a significant milestone in our journey—the acquisition of invaluable data from the **Deputy Commissioner of Police, Traffic East, Ahmedabad City.**

The path to obtaining this dataset was not a mere transaction but a story of cooperation, trust, and shared objectives. It began with a humble request for access to the real-world traffic data that would serve as the foundation of our project. Through the letter and the guidance, we had the privilege of delivering our request in person to the **honourable Commissioner of the Police Department.** It was a moment filled with anticipation and hope a moment where we realized the significance of the trust that had been placed in us.

With the dataset in our hands, we embarked on the arduous journey of dataset preparation, model training, and system development. The data provided by the Ahmedabad Traffic Police Department became the bedrock upon which our ANPR and FRS systems were built. It was the essence of real-world traffic scenarios, the foundation upon which our models learned and thrived.

As we stand at the culmination of this project, we extend our heartfelt gratitude to the **Deputy Commissioner of Police, Traffic East, Ahmedabad city, and the entire Traffic Police Department.** Your trust in us, your support, and your commitment to public safety have been instrumental in our success. This project would not have been possible without your invaluable contribution.