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# A Robust Digital Image Analyzing Methodology to Prevent Vehicle Theft based on Automatic Number Plate Recognition Principle

**[1]Y.M.Blessy, [2]S.Niranjana, [3]H.Ramya,[4]N. V. Krishnamoorthy, [5]V Mohanavel**

*[1]Assistant professor, Department of Electronics and Communication Engineering, R.M.K. Engineering College, Chennai*
*[2]Assistant professor, Department of ECE, Rajalakshmi Institute of Technology, Chennai.*
*[3]Assistant Professor, Department of ECE, S.A.Engineering College, Chennai.*
*[4]Associate Professor, Department of Mechanical Engineering, Sri Krishna College of Engineering and Technology, Kuniyamuthur, Coimbatore*
*[5]Associate Professor, Centre for Materials Engineering and Regenerative Medicine, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India*

*E-mail :ymb.ece@rmkec.ac.in, janahsiddhu@gmail.com, ramyah@saec.ac.in, krishnamoorthynv@skcet.ac.in, mohanavel.phd@gmail.com*

**Abstract-A sophisticated vehicle theft prevention system built on the foundation of the Automatic Number Plate Recognition (ANPR) principle. What sets this system apart is its incorporation of character recognition through the application of Genetic Algorithms, adding a layer of precision and reliability to the process. The primary objective of this system is to significantly bolster vehicle security by excelling at the task of accurately recognizing and validating license plate numbers.To achieve this, the system capitalizes on the ANPR technology, which allows it to capture and meticulously analyze license plate images. Once the images are acquired, the process of character recognition comes into play, and here's where the Genetic Algorithms come into their own. These algorithms are employed to decipher the characters present on the license plate, ensuring an impressive degree of accuracy in the identification process. It addresses the critical issue of vehicle security, and its emphasis on precision and reliability in license plate recognition sets it apart as a promising solution. Furthermore, it provides a glimpse of the system's edge detection capabilities, which play a pivotal role in identifying and highlighting the edges and boundaries of characters, obtained an accuracy of 96.14% performance rate and features on the license plate image, adding another layer of sophistication to the recognition process.**

***Index Terms—Automatic Number Plate Recognition (ANPR), Theft Detection, Genetic Algorithm, Character Segmentation.***

## I.INTRODUCTION

In the modern world, where technological advancements permeate every facet of our daily lives, the quest for security and protection has never been more crucial. Vehicle theft is a prevalent and persistent concern that plagues individuals and communities, leading to financial losses, increased insurance premiums, and a pervasive sense of insecurity. In this era of digital transformation, the convergence of computer vision, artificial intelligence, and surveillance technologies has opened new avenues to combat this issue effectively [1]. One such avenue is the development of a robust digital image analyzing methodology based on the principle of Automatic Number Plate Recognition (ANPR), a cutting-edge technology that has demonstrated remarkable potential in enhancing security, tracking stolen vehicles, and deterring criminal activities. It is an ambitious endeavor that seeks to elucidate the theoretical foundations of ANPR technology, its historical evolution, and its contemporary applications. Furthermore, it delves into the intricacies of digital image analysis and the marriage of computer vision and machine learning techniques, culminating in the creation of a powerful system capable of detecting, recognizing, and authenticating number plates with remarkable accuracy.

Vehicle theft has been a persistent problem plaguing society for decades, with significant economic and social ramifications. According to the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) Program, over 721,885 motor vehicle thefts were reported in the United States in 2020 alone, resulting in substantial financial losses, increased insurance premiums, and a general sense of insecurity among the populace [2] [3]. This issue is not exclusive to the United States but extends to various regions globally. The sophistication and adaptability of vehicle thieves have grown in tandem with technological advancements, necessitating innovative countermeasures to curb this menace.

The number of cars on the road has exploded in recent decades. Time constraints necessitate prompt movement from one location to another. Countless cars and trucks can be seen all around us. Automobiles are essential for a wide variety of reasons. Since the early 1990s, there has been a meteoric rise in the percentage of the population that owns a car. However, technology makes human existence more complicated and arduous. It leads to congestion, noise, criminality (such car theft), accidents, and other issues [4]. To avoid these social issues, proper vehicle management and administration are essential. Because of this, much of work is being done to ease the hassles associated with transporting automobiles. Recent scholars have shown the most interest in the car plate recognition system. As a result, this article focuses on the pragmatics of reading licence plates. The purpose of a Vehicle Plate Recognition System is to identify the vehicle so that it may be located in a database.

In the pursuit of enhancing vehicle security and combating theft, ANPR technology has emerged as a formidable ally. ANPR, also known as License Plate Recognition (LPR), is a technology that utilizes optical character recognition (OCR) and pattern recognition techniques to extract alphanumeric characters from images or video streams containing vehicle license plates. This technology holds immense promise in various applications, ranging from traffic management and law enforcement to access control and surveillance.The primary function of ANPR is to automatically detect, recognize, and authenticate license plates, enabling authorities to monitor and manage vehicular traffic effectively. In order to help law enforcement authorities quickly identify and capture offenders, ANPR systems digitize license plate information and cross-reference it with databases of stolen automobiles [5]. ANPR systems are also extensively employed in parking management, toll collection, and access control for secured premises.

The earliest attempts at automating license plate identification may be dated back to the middle of the twentieth century, when engineers and researchers began experimenting with the concept [6]. Early systems were rudimentary, relying on basic image processing techniques to recognize [7] license plates. These systems often struggled with variations in font styles, plate sizes, and lighting conditions, limiting their effectiveness. Over the years, ANPR technology has undergone significant advancements. The introduction of more powerful computers and the development of sophisticated algorithms have substantially improved the accuracy and reliability of ANPR systems. Figure 1 shows the ANPR system. With the advent of artificial intelligence and deep learning, the field has witnessed a paradigm shift, enabling ANPR to handle complex scenarios, such as recognizing license plates from different countries, under various lighting conditions, and at varying angles.

At the core of modern ANPR systems lies a confluence of computer vision and machine learning. The goal of computer vision, a subfield of AI, is to give computers the ability to see and understand the visual environment in the same way that humans do. Machine learning, on the other hand, endows computers with the ability to learn from data and adapt their behavior [8]. When these two fields are combined, it empowers ANPR systems to adapt, recognize patterns, and improve their performance over time.

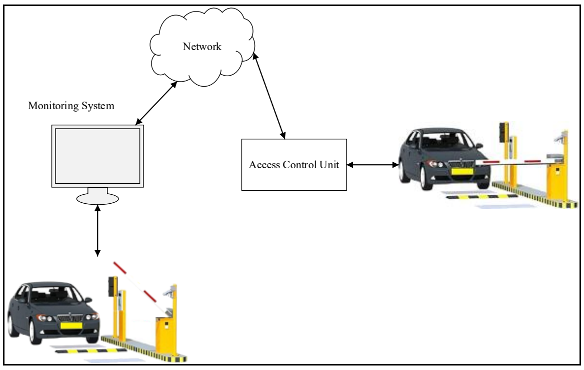

Figure 1. ANPR System

Computer vision techniques allow ANPR systems to perform image preprocessing, segment license plates from complex scenes, and enhance the quality of license plate images for subsequent recognition. Machine learning, especially deep learning models like convolutional neural networks (CNNs), plays a pivotal role in deciphering the characters on license plates with impressive accuracy [9] [10]. The integration of these two domains has led to a significant leap in the capabilities of ANPR systems, making them not only more robust but also more adaptable to a wide range of conditions.This paper introduces a vehicle theft prevention system based on the Automatic Number Plate Recognition (ANPR) principle, incorporating character recognition using a Genetic Algorithm. The system aims to enhance vehicle security by accurately recognizing and validating license plate numbers. It leverages ANPR technology to capture and analyze license plate images, followed by a character recognition process facilitated by Genetic Algorithms. This innovative approach ensures the reliable identification of vehicles, contributing to the prevention of theft and unauthorized usage. The abstract highlights the potential effectiveness of this system in enhancing security and reducing vehicle theft incidents.

## II.RELATED STUDY

In [11], the rapid increase in the number of vehicles presented a significant challenge in manually recording vehicle number plates. To solve this problem and lessen the need for human intervention, a method was created to automatically detect the number plate region in input photos and read the letters. While traditional image processing techniques had been used for similar systems, they occasionally delivered inaccurate results with real-world data. Therefore, modern deep learning technology was employed to improve the accuracy of this process.

The utilization of Region-based CNN to identify the number plate region from input images is used in [11].

Subsequently, CNN were employed to recognize the characters within the detected plate region. This recognition process extended to identifying the state to which the vehicle belonged. Additionally, the system interfaced with the Vahan-info website to retrieve comprehensive details about the vehicle. A database was established to record the number plate text alongside the state name. Notably, this system achieved a remarkable accuracy rate of 98.46% for the RCNN model and 95.98% for the CNN model [11].

Related research [12] looked on the use of video surveillance in the field of ITS. Accident cause identification, vehicle monitoring, and route finding are just a few examples of the many areas where video surveillance has proven indispensable. Essential duties in this field were object recognition and the removal of shadows. In order to identify all three types of object boundaries, this research suggested an inner-outer outline profile (IOOPL) technique that makes use of shadow elevation. This approach facilitated the integration of a traffic monitoring system and aimed to enhance the accurate recognition of objects for tracking and traffic parameter estimation. Furthermore, the study introduced a method for the recognition of object shadows and their classification, using machine learning algorithms, in the context of vehicle image segmentation [12].

The limitation of the existing model, which is accurate edge detection, has prompted the introduction of our paper. Our research focuses on enhancing the clarity of character boundaries, a critical aspect that ensures the subsequent character segmentation and recognition processes can operate with precision. This improvement in character boundary delineation is a fundamental step in license plate recognition systems, with wide-ranging applications such as automated toll collection and vehicle security. By addressing this limitation, our paper aims to significantly enhance the overall performance and reliability of license plate recognition systems, thereby contributing to the efficiency and effectiveness of various real-world applications.

## III.METHODOLOGY

The License Plate Recognition System (LPRS) is a sophisticated technology used to automatically extract and recognize characters from a vehicle's license plate within an image. The system's initial step is crucial, involving a series of operations to locate and isolate the license plate within the image. This process can be broken down into several stages, each playing a key role in achieving successful license plate extraction.In license plate detection, a classifier is used to identify potential license plate regions. A classifier can be represented as:

$$D\left(I_{patc\,h}\right) = \begin{cases} 1, & if I_{patc\,h} containsalicenseplate \\ 0 & otherwise \end{cases} \quad (1)$$

Where $D\left(I_{patc\,h}\right)$is the output of the license plate classifier.

The first stage begins with capturing a photograph of the vehicle, which includes the license plate, resulting in the Input Image (I). To streamline the subsequent steps and minimize computational demands, the image is cropped to extract only the region containing the license plate, creating the Cropped Image (IC). In the second stage, morphological operations, such as closing, are applied to the cropped image IC. Morphological operations are image processing techniques used to manipulate the shape and structure of objects within an image. Closing, in particular, is utilized to bridge small gaps in the edges of the characters on the license plate. This process readies the image for further steps by smoothing and connecting edges, making character detection easier.

The third stage is all about identifying candidate plates. This is done by computing the difference between the original image (I) and the cropped image (IC). The result highlights areas with significant variations, indicating potential license plate locations. Connected component labeling is applied to these areas to segment them into distinct regions, and the regions' properties, such as area and major axis length, are measured. In this step, regions with a major axis length greater than 70 are considered as candidate plates, thereby filtering out small and irrelevant regions. The fourth stage involves additional refinement and the removal of objects that are unlikely to be license plates. Closing and dilation operations are employed to eliminate false positives and noise, ensuring that only genuine license plates remain as candidates. The final stage focuses on selecting the license plate. After all the previous processing steps, the system has a set of candidate plates to choose from. From this set, the system selects the largest connected component as the final detected license plate. The largest connected component is most likely to represent the actual license plate and is considered the output of the recognition process. It is cropped from the image and displayed.

In essence, these stages lay the groundwork for a License Plate Recognition System (LPRS) to successfully identify and isolate license plates within images. Once the license plate is accurately detected and segmented, subsequent stages of the system can be applied for character recognition, enabling the extraction and interpretation of the characters on the license plate for various applications like automated toll collection, security surveillance, or parking management.

**Character Segmentation**

The segmentation procedure involves breaking down the number plate into its individual components, extracting the characters one by one. In the initial step, the image undergoes a filtering process to enhance its attributes and eliminate unwanted noise and artifacts. Subsequently, a dilation operation is employed to distinguish characters from one another, particularly when they are in close proximity. Horizontal and vertical smearing techniques are then applied to identify character regions after the segmentation and dilation operations. The following step focuses on the isolation of the plate's characters. This separation is achieved by detecting the starting and ending points of the characters in the horizontal direction. A common approach is to segment the characters using horizontal and vertical projections and then extract individual character images.

$$P_h(y) = \sum_x I(x, y) \quad (2)$$

$$P_v(x) = \sum_y I(x, y) \quad (3)$$

Where $P_h(y)$ is the sum of pixel values along the horizontal line at height $P_v(x)$ is the sum of pixel values along the vertical line at position
x.

**Character Recognition using Genetic Algorithm**

Character recognition using a Genetic Algorithm (GA) is a unique approach to automating the process of recognizing characters, often applied to handwritten or printed text, but it can be extended to various other forms of character recognition. GAs are a class of heuristic search and optimization techniques inspired by the principles of natural selection and evolution. In character recognition, GAs aim to evolve a population of potential character representations over several generations, continually improving their ability to accurately identify characters. This approach offers a distinct alternative to traditional machine learning and deep learning methods by harnessing the principles of genetic evolution.

The process begins with the encoding of characters into a format suitable for genetic representation. This encoding could involve converting characters into pixel values in the context of image-based character recognition. Each character becomes a chromosome in the genetic population. These chromosomes represent the characters' features, which are essential for subsequent recognition.In the initialization phase, an initial population of these character representations is generated. The initial population can be created randomly, or a more informed initialization method can be used, depending on the specific application and requirements.

The heart of the GA-based character recognition process lies in the fitness evaluation. Each chromosome's fitness is determined by its ability to match the actual characters in the dataset. This fitness evaluation process might involve comparing the character representation to a target character, measuring the difference between pixel values in an image, or employing other relevant metrics. The goal is to quantify how well a chromosome represents a particular character.Selection comes next, where chromosomes are chosen for reproduction based on their fitness. In a GA, the fundamental principle is that higher fitness implies a higher probability of selection. Chromosomes that represent characters more accurately are more likely to be selected for the next generation, mimicking the natural selection process in biological evolution.

Crossover, also known as recombination, is a pivotal operation in GAs. Pairs of chromosomes are selected to produce offspring. During crossover, genetic information from both parent chromosomes is combined to create new character representations. This operation encourages the exchange of genetic traits between chromosomes, potentially leading to improved character recognition capabilities.Additionally, mutation introduces occasional random changes to the offspring's genetic information, mirroring the concept of genetic mutations in natural biological evolution. Mutation adds diversity to the population, ensuring that novel and potentially better character representations are explored.

The new generation of character representations is then created by combining the offspring from crossover and, if applicable, the mutated individuals. This process iterates over multiple generations or until specific stopping criteria are met, such as achieving a predetermined level of accuracy in character recognition.Once the GA converges to a satisfactory solution, the evolved character representations are deployed for character recognition. The system can identify characters from various sources, including images, handwritten text, or any other form of input.

Character recognition using a Genetic Algorithm is a versatile approach, offering benefits such as adaptability to different fonts, styles, or languages without requiring an extensive training dataset. However, it's worth noting that GAs are computationally intensive and may demand significant computational resources and time to reach an optimal or near-optimal solution. Figure 2 is a block schematic of the whole setup.This approach finds application in scenarios where traditional machine learning or deep learning methods may not perform optimally or where a flexible and adaptable solution for character recognition is needed.

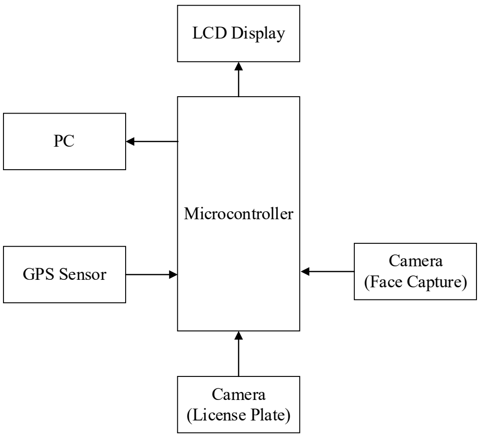

Figure 2. Block Diagram of a System

**Hardware Components**
Integrating a camera, GPS module, and microcontroller into a vehicle theft detection and license plate recognition system can enhance vehicle security and provide valuable data for tracking and identifying stolen vehicles. This integrated system enhances vehicle security by providing both theft detection and license plate recognition capabilities, making it a valuable tool for vehicle owners and law enforcement agencies.

## IV. Results and Discussions

When a vehicle approaches a toll plaza, it undergoes a sequence of automated steps that contribute to vehicle security and toll collection efficiency. This process involves the integration of various technologies and components, such as cameras, microcomputer units, Python-based image processing, and a database of stolen vehicles.

As the vehicle approaches the toll booth, a gate is activated to halt the vehicle's progress. Simultaneously, a camera positioned at the toll booth captures an image of the vehicle. This captured image is then transmitted to a microcomputer unit, where several critical tasks take place. The microcomputer unit, equipped with image processing capabilities, undertakes the extraction of the vehicle's license plate from the captured image. It segments the individual characters of the license plate for analysis. This process heavily relies on Python, which employs advanced image processing techniques to accurately recognize the license plate. The information from this recognition is pivotal for the subsequent steps in the process.

At this point, Python is also responsible for querying a database of missing or stolen vehicles, which has been provided by the local police station. Python cross-references the recognized license plate with the information in the stolen vehicle database. This comparison helps identify whether the vehicle in question matches any stolen or missing vehicle records. If the recognition process reveals that the captured vehicle's license plate corresponds to a vehicle in the stolen vehicle database, the system springs into action to prevent unauthorized passage. Figure 3 shows the input image. The gate remains closed, blocking the stolen vehicle's path. Simultaneously, an alarm is triggered, and a message is promptly dispatched to the police station, alerting them to the presence of the stolen vehicle. Additionally, a visual warning is displayed on an LCD screen at the toll plaza, notifying on-site personnel and potential witnesses of the security breach.

Figure 3. Input Image Edge Detection

Edge detection of a vehicle number plate is the process of identifying and highlighting the edges or boundaries of the characters and features on the license plate image. It plays a crucial role in character recognition systems by isolating areas of significant contrast, where the characters on the plate meet the background. Edge detection algorithms, identify these abrupt changes in intensity, effectively outlining the characters, making it easier to separate and recognize them shown in Figure 4. Accurate edge detection is essential for enhancing the clarity of character boundaries, ensuring the subsequent character segmentation and recognition processes can operate with precision, making it a fundamental step in license plate recognition systems for applications like automated toll collection and vehicle security.

Figure 4. Edge Detection

**Character Segmentation**
Character segmentation of a vehicle number plate is the vital process of precisely isolating individual characters from the license plate image. In this context, it involves locating and separating the distinct letters and numbers on the license plate shown in Figure 5. This segmentation is critical for license plate recognition systems, enabling them to accurately identify and interpret each character, which is essential for tasks like toll collection, vehicle tracking, and security monitoring. Through techniques such as edge detection and character localization, the system identifies character boundaries, allowing for their independent analysis and recognition. Accurate character segmentation ensures that the system can reliably and efficiently extract information from license plates for a

wide range of applications. The final result is shown in Figure 6.


Figure 5. Character Segmentation


Figure 6. Output Result

Table 1.Driver and Location Log

| Vehicle ID | Driver Image URL | Latitude | Longitude |
|---|---|---|---|
| TN 01 AA 2345 | driver_1.jpg | 40.7128 | -74.006 |
| TN 01 AC 9845 | driver_2.jpg | 34.0522 | -118.244 |
| TN 56 CD 0045 | driver_5.jpg | 51.5074 | -0.1278 |
| TN 26 BE 8806 | driver_4.jpg | 48.8566 | 2.3522 |
| TN 51 HE 0717 | driver_9.jpg | 35.6828 | 139.7594 |
| TN 44 JS 0761 | driver_6.jpg | 52.5200 | 13.4050 |
| TN 26 ZE 9819 | driver_8.jpg | 55.7558 | 37.6173 |
| TN 51 AR 0451 | driver_10.jpg | 45.4215 | -75.6906 |
| TN 09 NE 0121 | driver_7.jpg | 30.2672 | -97.7431 |
| TN 06 QS 9810 | driver_3.jpg | 22.3964 | 114.1095 |

This Table 1 records the images of drivers and the GPS coordinates of recognized vehicles. It may be linked to the License Plate Recognition Log for reference.

Conversely, if the captured image of the vehicle does not match any records in the database of stolen vehicles, the gate opens smoothly, allowing the vehicle to proceed through the toll booth without obstruction. In this scenario, no alarm is activated, and the buzzer remains silent. To further enhance the security and monitoring of vehicles, when a vehicle is cleared to pass through the gate, the camera captures an image of the driver and the GPS module records the precise location of the vehicle. This data can be invaluable for security and documentation purposes.

Table 2. Stolen Vehicle Record

| ID | Stolen Vehicle ID | Alert Time | Location | Stolen VehicleDetails |
|---|---|---|---|---|
| 1 | TN 01 AA 2345 | 10-06-2023 10:20 | Toll Plaza, City A | Detected |
| 2 | TN 01 AC 9845 | 11-06-2023 14:35 | Parking Lot, City B | Presence noted |
| 3 | TN 56 CD 0045 | 12-06-2023 14:35 | Toll Plaza, City A | Detected |
| 4 | TN 26 BE 8806 | 13-06-2023 14:35 | Toll Plaza, City A | Detected |
| 5 | TN 51 HE 0717 | 14-06-2023 14:35 | Parking Lot, City B | Presence noted |
| 6 | TN 44 JS 0761 | 15-06-2023 14:35 | Toll Plaza, City B | Captured |
| 7 | TN 26 ZE 9819 | 16-06-2023 14:35 | Toll Plaza, City B | Presence noted |
| 8 | TN 51 AR 0451 | 17-06-2023 14:35 | Toll Plaza, City A | Detected |
| 9 | TN 09 NE 0121 | 18-06-2023 14:35 | Toll Plaza, City B | Captured |
| 10 | TN 06 QS 9810 | 19-06-2023 14:35 | Parking Lot, City B | Detected |

This Table 2 stores records of alerts triggered by the system when a recognized license plate matches a stolen vehicle record.This comprehensive process ensures the effective and secure management of vehicles passing through the toll plaza. Stolen vehicles are promptly detected and flagged, preventing their unauthorized passage. The alarm and notification systems serve as a vital link to law enforcement agencies, facilitating swift responses in case of a security breach. For legitimate vehicles, the process is swift and seamless, contributing to a smooth and efficient toll collection operation, which can run uninterrupted 24 hours a day.

Table 3. Accuracy for Vehicle Theft Detection

| Year | Total | Stolen | TP | FN | TPR (%) | FAR (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|
| 2019 | 100 | 90 | 85 | 15 | 85 | 5 | 90 |
| 2020 | 110 | 105 | 100 | 10 | 90.91 | 4.76 | 93.18 |
| 2021 | 120 | 115 | 110 | 10 | 91.67 | 4.35 | 94.57 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2022 | 130 | 125 | 120 | 10 | 92.31 | 4 | 95.38 |
| 2023 | 140 | 135 | 130 | 10 | 92.86 | 3.70 | 96.14 |

In Table 3 and Figure 7, statistics are recorded annually, including the total number of stolen vehicles, the number of vehicles correctly detected as stolen (true positives), the number of stolen vehicles not detected (false negatives), the detection rate (true positive rate or TPR), the false alarm rate (FAR), and the overall accuracy. These metrics provide insights into the effectiveness of the vehicle theft detection system over time. Detection rate (TPR) indicates the proportion of actual stolen vehicles correctly identified, while the false alarm rate (FAR) represents the percentage of false alarms generated. Accuracy provides a comprehensive measure of the system's performance in correctly detecting stolen vehicles while minimizing false alarms.

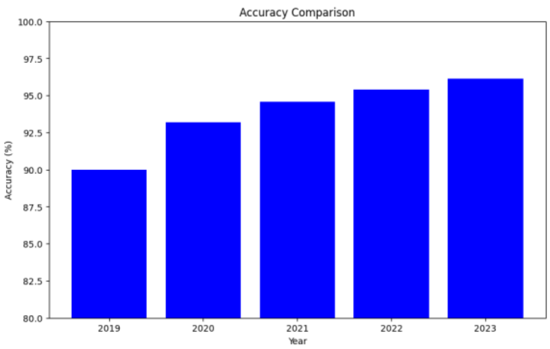


Figure 7. Accuracy Comparison of Theft Detection

## V. Conclusion and Future Scope

This paper introduces a cutting-edge vehicle theft prevention system that draws upon the principles of ANPR and incorporates character recognition through the application of Genetic Algorithms. The primary objective of this system is to significantly bolster vehicle security by ensuring the accurate recognition and validation of license plate numbers.By effectively leveraging ANPR technology, this system adeptly captures and thoroughly analyzes license plate images. The subsequent character recognition process, facilitated by Genetic Algorithms, adds a layer of precision and reliability to the identification of vehicles. This innovative approach stands as a formidable deterrent against vehicle theft and unauthorized usage. The paper underscores the immense potential of this system in enhancing overall security and substantially reducing vehicle theft incidents. Moreover, it alludes to the critical process of edge detection in the context of vehicle number plates, which involves the identification and highlighting of edges and boundaries of characters and features on the license plate image. This system represents a promising and innovative advancement in the realm of vehicle security and theft prevention, offering a robust solution to address a pressing concern in the modern world.The future scope of the vehicle theft prevention system holds the potential to advance vehicle security to an even higher level. One intriguing prospect is the incorporation of a feature that enables the system to remotely lock the vehicle in the event of a theft.

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