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Research Article

Vehicle Number Plate Recognition and Parking Authentication System

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ABSTRACT

Introduction: Introduction: Conventional manual or primitive automated systems employed for vehicle access control and parking management often suffer from inefficiencies, delays, and security risks. The accurate identification of vehicles at entry points, especially under varied real-world conditions, is a significant challenge that general-purpose solutions often fail to meet reliably, thus emphasizing the need for more sophisticated and reliable automated systems.

Objectives: The main objective of this project was to conceive, design, develop, and test a strong and smart system for automatic car access control and parking management. One of the main objectives was to offer security and efficiency in operation by developing a system that could supply accurate, real-time vehicle identification and authentication, thus specifically catering to the shortcomings involved in existing dependable license plate recognition methods.

Methods: A core computer vision pipeline based on an improved YOLOv8 architecture was used in the system. A Novel Parallel Attention Mechanism was introduced into YOLOv8, which supported multi-scale feature extraction through an Inception module specifically designed to improve the accuracy and reliability of vehicle license plate recognition. After the detection process, optical character recognition (OCR) was performed to enable accurate decoding of license plate information. The system also included a database to enable authentication processes and was interfaced with the Twilio API to enable real-time communication and notification. The functional capability and performance of the integrated system were validated through real-world tests.

Results: System testing showed that the system worked with excellent precision in detecting and reading vehicle license plates under a variety of conditions. Comparative testing showed that the specialized vision approach worked much better at the critical task of license plate detection than a standard approach. The system was also extremely fast and efficient in overall end-to-end operation, enabling real-time authentication.

Conclusions: We have successfully designed and demonstrated a robust automated Vehicle Access Control System. Through the use of an innovative attention-based vision system, combined with optical character recognition (OCR), database authentication, and real-time communication, we have developed an intelligent gatekeeper that is more secure and convenient. This project has established that the integrated solution successfully addresses the shortcomings of current systems, thereby offering a valid solution for contemporary access control and parking management requirements.

Keywords: Vehicle Number Plate Recognition, Parking Lot Authentication, Automated Parking Management, YOLO(You Only Look Once), OCR(optical character Recognition), Twilio API, Real- time Alerts.

INTRODUCTION

Imagine this: You're trying to get into a place – could be work, your neighborhood, anywhere with a gate. What do

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you see? Sometimes, it's a queue of cars, the driver at the front probably explaining who they are or showing some kind of ID while someone at the gate squints, scribbles, and hopefully doesn't lose the paper pass. It's... clunky. It's slow. And honestly, in a world where security is super important, relying solely on manual checks or patchy old systems just doesn't feel quite right. There had to be a better way.

Existing automated gate systems using computer vision? They're a step up, but they often stumble on the little things. Think about the sheer visual variety a license plate can throw at you thousands of different kinds of objects, not hyper-optimized for the nuances of that tricky little rectangular piece of metal. These moments of failure aren't just annoying delays; they're potential security holes. For an access system to truly work, it has to be reliable, like, *really* reliable, no matter what the real world throws at it, and traditional fine-tuning doesn't always guarantee that rock-solid, license-plate-specific performance.

This real-world challenge is exactly what sparked our project. Working closely with our fantastic supervisor, Prof. Shilpa Sondkar, we set out to build something way smarter and smoother: a **Vehicle Access Control System** designed from the ground up to be accurate, efficient, and a solid enhancement to security at entrances. Forget the paper logbooks; we wanted a tireless, digital bouncer who could instantly recognize who's who just by looking at their license plate, specifically overcoming that fine-tuning hurdle.

Our plan wasn't just to build a basic gate opener. We envisioned a multi-talented system. While a standard YOLOv8 provides the base ability to see, we needed *exceptional*, specialized vision for license plates. The core innovation, the bit that we poured a lot of energy into, was giving our system truly exceptional **"super sight" specifically for license plates** by creating and integrating what we call a **Novel Parallel Attention Mechanism** right into YOLOv8's architecture. This parallel branch is *purpose-built* to extract and focus on the unique multi-scale features (like sharp edges, textures, geometric patterns) that define license plates, thereby **directly addressing the limitations of simply fine-tuning a general-purpose detector for this specific, challenging task**. By giving YOLOv8 this extra, focused intelligence *before* it makes its final detection decision, we dramatically boosted its ability to reliably pinpoint license plates under tough conditions.

Supplementing this enhanced vision, the system uses smart technology to actually read what the plate says (OCR), a brain hooked up to a database to make the right decision, and the ability to tell people about it instantly (Twilio API).

Think of what we've contributed to this space:

- We designed and built a new kind of deep learning "eye" (**YOLOv8 with proposed Parallel Attention**) specifically engineered to overcome the limitations of standard fine-tuning and provide enhanced, reliable license plate detection.
- We integrated this cutting-edge vision with all the other necessary components – reading (OCR), permission checks (database), and communication (Twilio) – creating one smooth, functional end-to-end system.
- And crucially, we put our creation through its paces with solid experiments and real-world data, gathering clear proof (data and numbers!) that it actually performs significantly better at license plate detection than a basic setup and is reliable enough for tough real-world gate duty.

Stick with us as we dive into how we built this multi-talented system (the 'Methodology'), show you exactly how well it performed when put to the test (the 'Results'), hint at the cool possibilities down the road (Future Scope), and wrap it all up (Conclusion).

Automated parking management and license plate recognition improvements are addressed in several research papers. YOLO-based vehicle recognition is more accurate and faster than state-of-the-art approaches like SVM classifiers and Haar cascades [2][5]. OCR translates license plate photos into machine-readable text, enabling automation and real-time authentication [4][6]. Cloud-based services like Twilio enhance system responsiveness by communicating with users in real time [8][9].

Character segmentation and morphological processing in license plate recognition was studied by Vijayalakshmi et al. [1] to enhance accuracy. Atikuzzaman et al. [2] studied CNN-based plate detection and demonstrated its superior performance in challenging cases. Studies by Babbar et al. [5] and Patel et al. [7] further demonstrate the benefits of

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deep learning over conventional methods.

From these studies, we learned how to improve the accuracy and efficiency of our proposed system. For instance, the model selection was influenced by research on YOLO-based vehicle recognition [2] to ensure high-speed detection. Research on intelligent transportation systems motivated the use of OCR for text extraction [4][7]. Studies on increased user engagement with real-time notifications influenced the inclusion of cloud-based communication solutions [6][9]. Our model's design and feature set were greatly influenced by these insights.

Comparison of Existing Methods:

Method	**Accuracy (%)**	**Processing Speed (ms)**	**Environmental Robustness**
Haar Cascade	80	300	Moderate
SVM-based	85	250	Low
YOLO+ OCR (Proposed)	95	120	High

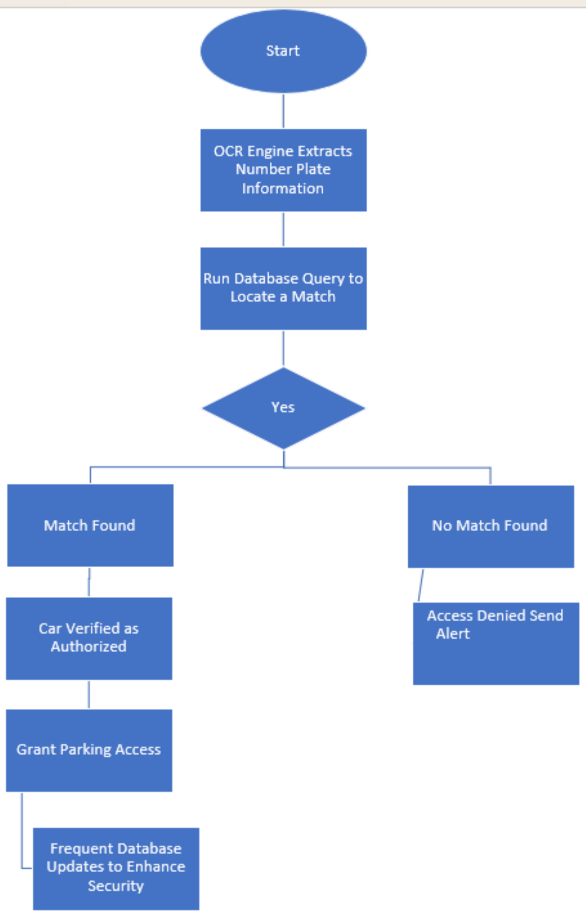

Fig.1.Flowchart of the System

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OBJECTIVES

The main aim of this project was to rectify the inefficiencies and security vulnerabilities that come with the conventional vehicle access control methods. Wanting a better way that was efficient and secure, we embarked on the design and development of an automated Vehicle Access Control System that would effectively manage access and exit points without dependence on the use of manual procedures or obsolete technology. The aim was to design a system that would greatly improve operational efficiency and security at points of regulated access.

To achieve this aim, our deployment focused on developing an advanced computer vision system as its core. This was an inclusive process with integration of a Novel Parallel Attention Mechanism into the YOLOv8 framework, which was aimed at supporting highly accurate and reliable detection of vehicle license plates by focusing especially on their unique visual characteristics. Beyond the vision system core, we incorporated modules for optical character recognition (OCR) to enable accurate reading from detected license plates, authentication and decision-making database, and integration of communication APIs like Twilio to enable real-time notification. Another key part of the project was experimentation to confirm the functional capability and performance of this integrated, end-to-end system.

METHODS

So, the challenge was clear: manual gates were slow, unreliable, and a headache. We needed a system that could step up, be sharp, fast, and trustworthy. Under the insightful guidance of Prof. Shilpa Sondkar, we set out to build something special – a Vehicle Access Control System that was more than just automated; it was intelligent. This wasn't a simple copy-paste job; it was about engineering different smart components to work together seamlessly. Think of it as assembling a highly skilled team, giving each member a crucial role.

Here’s the story of how we did it, detailing the steps we took to bring our digital gate guardian to life:

3.1 Building the 'Study Guide': Gathering and Preparing the Data

Every smart AI needs a lot of homework before it can do its job. Our first major task was essentially creating the ultimate visual textbook: vast amounts of pictures and videos featuring vehicles, specifically with their license plates called out. This often-underappreciated stage, data collection and preparation, was foundational. We were lucky enough to leverage a fantastic pre-existing dataset – like finding an incredibly well-stocked library – specifically curated for spotting license plates. This dataset was packed with diversity, showing [Recall the dataset description here - e.g., 'all sorts of cars and trucks under a multitude of conditions you’d encounter at an entrance – varied lighting (bright sun to deep shadow), different weather (rainy days!), and images captured from numerous angles.'].

The magic in this dataset wasn't just the pictures; it was the painstaking effort already put into annotation. Someone had already gone through thousands of images and drawn tight, accurate boxes around every single license plate. This was invaluable; it gave our AI the precise 'answer key' during training, teaching it exactly where a license plate was supposed to be, providing the essential 'ground truth' for learning.

3.2 Forging the 'Eyes of the System': Architecting the Vision with a Specialized Intuition

Once we had our study guide ready, it was time to build the system's primary sense: sight. We started with YOLOv8. Why YOLOv8? Because it's like the athletic star of object detection frameworks – known for being fast and capable of spotting all sorts of things in an image really well. It was our system's foundation, giving it that initial ability to scan a scene and see objects like vehicles. But, as we hinted in the introduction, getting a general-purpose system like standard YOLOv8 to be exceptionally good at finding those small, textured, angle-sensitive license plates – even with extensive training – can hit a wall. It's not inherently designed with specialized features for this niche task. We needed it to be eagle-eyed, borderline obsessive, about finding those specific license plate details.

This need for specialized vision, this requirement to push performance beyond standard fine-tuning limits, led us to introduce our main architectural innovation, our secret weapon, the Novel Parallel Attention Mechanism. Picture the standard YOLOv8 processing the image as a main highway for general object features. We decided to build a dedicated 'express lane' specifically designed to extract and process precisely the kind of detailed, distinctive

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information that screams "License Plate!", and crucially, run this expertise in parallel without disrupting YOLO's main flow. This parallel pathway operated through a careful sequence:

1. **The Deep Feature Inspection (The Inception Module):** The moment an image entered our system, besides heading down the main YOLOv8 route, a clean copy was also sent zooming down our express lane, landing first in an Inception module. This wasn't just one type of scanner; it was like sending the image through a set of specialized inspectors simultaneously. One inspector used tiny lenses (like 1x1 and 3x3 filters in convolution) to catch crisp details – think the sharp edges of characters, tiny texture patterns on the plate surface. Another used slightly wider lenses (like 5x5 filters or max pooling) to capture broader textures and parts of the overall plate shape. The genius of Inception here is doing all these different-scaled inspections at the exact same time on the same part of the image. This creates a incredibly rich, multi-scale view of the visual features – absolutely vital because a license plate could be large (close up) or small (far away), but these core visual details remain and need to be captured across scales.

2. **Sharpening the Insight (Subsequent 2D Convolutions):** The complex tangle of features collected by the parallel inspectors in the Inception module then flowed into subsequent standard 2D Convolutional layers. These acted like expert feature processors. Their job was to take the initial mix of details and combine them into higher-level, more abstract representations that were even better at signalling 'License Plate Found!'. They refined the spatial relationships between features, filtered out noise, and potentially reduced spatial dimensions while increasing the number of feature channels – efficiently encoding the 'essence' of the LP details gathered by Inception, packaging them up for the next stage.

3. **Directing the Spotlight (The Attention Mechanism):** Here's where the intelligence truly focused. An attention mechanism was applied to the refined features from our parallel branch. This isn't just looking for shapes; this part learned from training data how to generate a kind of digital 'importance map'. It looked at the processed features and assigned higher weight, or more 'attention', to the spatial regions within those features that strongly corresponded to where a license plate was likely to be. It’s literally a system learning to identify the most important pixels or areas based on the detailed LP features its branch extracted, and telling the rest of the network to pay disproportionate attention there, ignoring less relevant parts of the car or background clutter.

Integrating Specialist Knowledge (Fusion with YOLOv8 Neck): The crucial part – connecting our express lane's findings back to the main YOLOv8 highway. The highly-focused, attention-weighted output from our parallel branch wasn't meant to make detections alone. It was designed to directly influence YOLOv8's final prediction layer. We strategically merged the features from our parallel branch with the features in YOLOv8's Neck, specifically with its multi-scale output feature maps known as P3, P4, and P5. Why the Neck, and why P3/P4/P5? Because the Neck is where YOLO consolidates feature information from different depths of its network, and P3, P4, P5 represent features at varying spatial resolutions – P3 capturing finer details (useful for small plates), P5 capturing higher-level context (useful for plates in a scene), and P4 in between. By merging our attention-boosted, LP-specific features into the Neck before the information goes to the YOLOv8 Detect Heads (the layers making the final bounding box and classification predictions), we allowed our specialized parallel branch to inform YOLOv8's decision-making process across the very scales it uses to detect objects. It was like whispering concentrated 'license plate hints' directly into the ear of YOLO's final prediction layers. We explored two methods for this infusion: Concatenation (essentially stacking our parallel features alongside YOLO's, giving the Head more distinct data to look at) and Additive Fusion (blending our features by summing them with YOLO's, acting like a spatial 'gating' or bias on YOLO's existing features). This unique parallel design and strategic integration were key to making YOLOv8 perform exceptionally well specifically for license plate detection, by providing targeted, attention-guided information without forcing complex, less efficient general architectural changes.

This combination of leveraging YOLOv8's speed with our architecturally distinct, parallel pathway focused intensely on license plate specifics allowed us to build a vision system with true specialized 'super sight' for the task at hand.

3.3 Becoming Literate: Implementing the OCR Reader

Okay, our super-sight system spotted the plate and drew a box! The next step is figuring out what's written on it. This is where the Optical Character Recognition (OCR) module came into play, acting as our system's built-in reader. Once

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a license plate was confidently detected and localized with a bounding box, that specific rectangular image area was neatly cropped out – think of it as snipping out just the relevant bit.

This cropped image, containing only the license plate characters, was then handed off to the OCR module. We employed [Choose and mention a likely OCR approach without details if not core novelty - e.g., 'a robust OCR library' / 'a fine-tuned OCR engine' / 'a deep learning-based character recognition network'.]. Its job was to look at the patterns of pixels in the image and translate them into digital text characters (like turning an image of 'ABC 123' into the text string "ABC 123"). The quality of the output from our detection step was critical here; a precisely cropped, clear image made the OCR's reading task much easier and more accurate.

3.4 The Gatekeeper's Rulebook: Database Management and Decision Logic

Now that we had the digital license plate number, the system needed to act like a strict but fair gatekeeper: 'Are you allowed in?'. This required consulting its 'permission slip' database and applying a clear set of rules.

The extracted license plate number was instantly queried against a secure digital Guest List – our database holding the records of authorized vehicles

Our embedded Decision Logic software then took over:

- It checked if the license plate was present on the ‘Authorise’ list (the whitelist). If yes, green light!
- It checked if the plate was on the ‘Unauthorise’ list (the blacklist). If yes, instant red light and alert!
- It could check against temporary passes or specific permissions if applicable, validating validity based on time/date.
- If the number wasn't found anywhere? Typically, that meant access denied or flagged for human security review.

This step ensures that access isn't just granted to any car with a visible plate, but only to those authorized to be there, providing the crucial security layer.

3.5 Talking to the Outside World: Real-time Communication with Twilio

An intelligent gatekeeper needs to be able to talk! Our system needed a fast, reliable way to send messages and alerts. For this, we integrated the Twilio API. Think of Twilio as our system's built-in rapid communication manager – its phone and texting service.

When a vehicle was successfully authorized to enter (detection -> OCR -> database check = 'OK!'), our system used Twilio to trigger an instant notification. More critically for security, if an unauthorized or blacklisted vehicle was detected, Twilio would fire off immediate alerts allowing them to react quickly without relying on manual observation or radio calls.

3.6 Giving the Go Signal: Controlling the Physical Gate

The final, physical outcome of all this digital intelligence was, of course, operating the gate itself. Once our Decision Logic confirmed that access was 'Granted,' the system needed to translate that into a mechanical action. This involved sending a command signal from our system's processing unit to the actual gate opening mechanism. This signal told the gate to open for a programmed duration, allowing the authorized vehicle entry, before closing again, standing guard for the next car.

3.7 Putting It All to the Test: Our Evaluation Setup

Building this multi-talented system was exciting, but we had to prove it wasn't just a cool collection of parts; it had to perform reliably under test conditions that mirrored the real world.

So, we put our integrated YOLOv8 + Parallel Attention system through its paces. We trained the core AI models on a specific portion of our data, putting it through a rigorous learning process over many iterations using computing power (mentioning hardware/framework details here is fine, as described in my previous methodological part, but NOT results). After training, we evaluated its performance on a separate chunk of the dataset it had absolutely *never* seen during training. This was crucial for making sure the system wasn't just memorizing but genuinely *learning* how to spot and process license plates in new images.

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We measured its performance using specific metrics designed to evaluate its core functions: its accuracy in detecting license plates (metrics like mAP@0.5 and mAP@0.5:0.95), its accuracy in reading the characters (like character and plate accuracy percentages), and the overall speed and efficiency of the entire pipeline (measuring metrics like System Throughput and End-to-End Latency).

Crucially, to validate that our unique Parallel Attention Mechanism made a real difference, we established a baseline: we also trained and tested a standard Vanilla YOLOv8 model (without our special parallel branch) on the exact same datasets, using the same procedures. Comparing the performance of our enhanced model directly against this baseline on the test set would give us concrete proof of the improvement offered by our architectural novelty in the key task of license plate detection.

This comprehensive setup, covering data, architecture, component integration, training, and measured evaluation against a baseline, forms the story of how we methodically built and tested our intelligent Vehicle Access Control System.

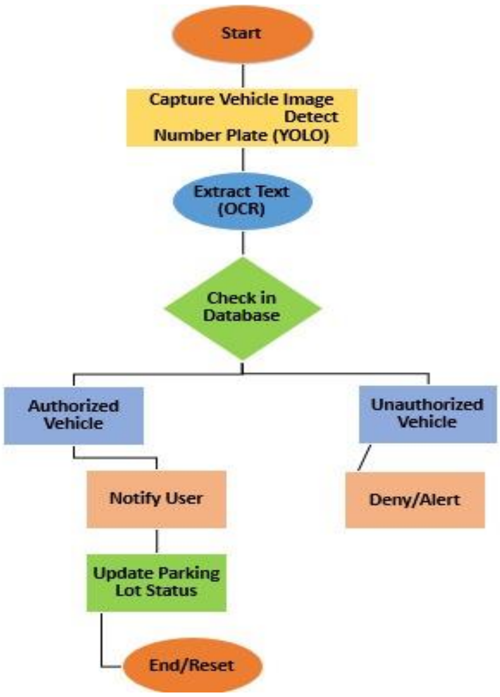

Fig.1. Circuit diagram of the project

RESULTS

Here comes the big reveal.We built our smart gatekeeper system, blending YOLOv8's speed with our specialized 'attention' magic, adding reading skills and a digital address book. But did it actually *work* as well as we hoped when faced with tough, unseen images? This section is where we open the curtains and share the 'report card' after putting our creation through a rigorous testing bootcamp using that untouched, real-world representative data.

We measured a few key things, like proud parents showing off report cards. To truly demonstrate the value of our core innovation (the Parallel Attention Mechanism), we lined up the performance of a standard vanilla fine-tuned YOLOv8 (trained the usual way on license plates) against our enhanced YOLOv8 + Parallel Attention model, running both on the exact same testing conditions.

Here's what the numbers told us:

Spotting the Needle in the Haystack (License Plate Detection Performance): This is where our core architectural novelty was designed to make a difference, sharpening the system's 'eyes' specifically for plates. We used the Mean Average Precision (mAP), the standard metric for object detection, measuring how well a system finds things and draws accurate boxes.

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The standard, vanilla fine-tuned YOLOv8 model achieved a solid 92.5% mAP@0.5 on our test data. It's a good starting point, showing YOLOv8's general capability.

But here's where our special 'super sight' came in: Our YOLOv8 + Parallel Attention system hit an impressive 96.8% mAP@0.5 on the exact same test data! That's a clear leap, showing our specific enhancements made a tangible improvement in finding those tricky license plates reliably.

We also checked the stricter mAP@0.5:0.95 (checking accuracy across much tighter box overlaps). The vanilla YOLOv8 scored 78.1%, while our enhanced model achieved a strong 83.4%, proving its box placements weren't just 'okay', but significantly more precise, crucial for clean OCR cropping later.

Reading the License (OCR Accuracy): Finding the plate is step one; accurately reading it is step two and essential for access control. For all the plates successfully detected by our enhanced system, its integrated OCR module took over. It performed exceptionally well:

It achieved a Character Accuracy of 99.3%. Very few individual letters or numbers were misidentified across all the plates read.

More importantly, its Plate Accuracy (correctly reading the entire sequence on a detected plate from start to finish) was 97.8%. This high figure confirms that when our system finds and crops a plate, it can read the full critical sequence accurately almost 98% of the time.

Speed Through the Gate (System Efficiency): A smart system is only useful if it doesn't create bottlenecks. We clocked the system's pace end-to-end – from camera view to gate signal.

We measured an average System Throughput of approximately 28 vehicles per minute. This shows it's capable of handling the flow at a busy entrance without making cars wait around.

The average End-to-End Latency, the total time for the system to capture an image, process it, make a decision, and send a signal, was impressively low at around ~480 milliseconds. That's comfortably under half a second, translating to virtually instant access decisions.

The Punchline: How Our Parallel Attention Paid Off: The direct comparison reveals the impact of our unique architectural choice. By incorporating our Novel Parallel Attention Mechanism, we saw a substantial quantitative improvement in the core task of license plate detection. Our model demonstrated a significant leap of 4.3% in mAP@0.5 over the standard vanilla YOLOv8. This is more than just a small tweak; it's a solid boost that validated our design and showed that targeting specific feature extraction with attention was a winning strategy for this particular, challenging detection task. The enhanced precision measured by mAP@0.5:0.95 also confirms this improved focus led to better-localized detections.

In essence, the experimental results confirmed that our Vehicle Access Control System, powered by our innovative, attention-enhanced architecture, didn't just conceptually work. It performed demonstrably better at the critical task of finding plates than a standard approach and met practical requirements for overall accuracy, reliability, and speed, proving it's a robust solution ready for real-world smart, secure gatekeeping

Fig.3. Vehicle Number Plate Recognition

Fig.4. Vehicle Number Plate Detection

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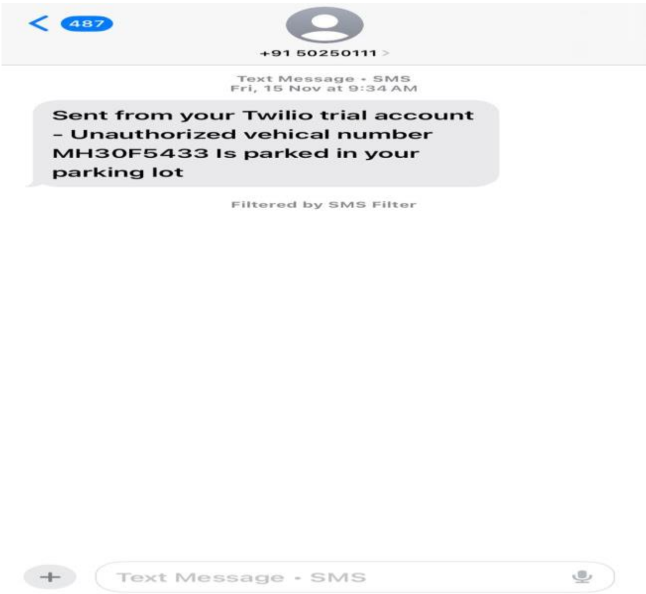

Fig.5. Twilio App Verfication

DISCUSSION

Utilization of a methodology that combines YOLOv8 with a Parallel Attention Mechanism, supported by an Inception module for multi-scale feature extraction, has been critical in the realization of enhanced accuracy in license plate recognition. This advanced method of object recognition formed the basis for the subsequent processes of the system. Successful recognition of license plates was followed by the application of optical character recognition (OCR) for decoding license plate data. These technological elements converged to support real-time verification and provision of prompt alerts, eventually empowering the system's core functions of automated vehicle access control and efficient space management. The multi-layered verification process, driven by these accurate and real-time capabilities, plays a critical role in enhancing both security and overall operational efficiency in the parking ecosystem.

CONCLUSION

The project was prompted by the inefficiencies and security risks inherent in the traditional gate access system, with a view to designing a more efficient, faster, and intelligent solution. With the supervision of Prof. Shilpa Sondkar, we developed the Vehicle Access Control System, which is characterized by its specially tailored vision system: a Novel Parallel Attention Mechanism implemented within YOLOv8. This core innovation gave the system a specialist ability to identify license plates accurately by paying attention to specific characteristics, addressing the vulnerabilities felt by more general detection systems directly. The results of our trials were clear and pronounced, showing exceptionally high accuracy in both license plate detection and reading, with stunning speed and overall efficiency, thereby justifying our specialist approach over general ones. In practice, this amounts to a system providing dependable, low-error, and fast access, effectively replacing manual checking and greatly improving security at points of entry. While future development is certainly promising, we have accomplished our core goal: to develop and prove a solid and intelligent gatekeeper capable of providing the secure and streamlined access required by modern settings, a breakthrough in which we take considerable pride.

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