A Cascaded Vision Transformer for Precise Identification of Vehicle Number Plate

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Abstract: Aim: The present investigation centers on the examination of License Plate Detection (LPD) methodologies employing Vision Transformer (ViT) technology to establish a sophisticated, efficient, dependable, and scalable framework for the real-time detection and recognition of vehicle license plates. The principal aim of this scholarly pursuit is to harness the capabilities of ViT to augment predictive precision in contrast to conventional Deep Convolutional Neural Networks (DCNN), which have been extensively utilized for analogous undertakings. The efficacy of the system is assessed by juxtaposing the performance of a ViT-based model with that of an independent DCNN model under uniform testing circumstances. The experimental analysis is segmented into two cohorts: Group 1, which encompasses ten distinct DCNN-based models evaluated for license plate detection, each exhibiting varying degrees of accuracy, and Group 2, which integrates an advanced ViT-based model specifically engineered for precise detection and recognition of vehicle license plates. The findings obtained elucidate that DCNN models achieve an accuracy range spanning from 84% to 90%, whereas the ViT model exhibits enhanced effectiveness with an accuracy range of 91% to 96%. The recently established ViT-based framework achieves an overall accuracy of 94.5%, surpassing the 90.00% accuracy of the individual DCNN model. The evaluation metrics include a maximum disparity of 10.50, a minimum of 2.00, a step increment of 0.10, and a significance level of $p < 0.05$. These findings substantiate the viability of ViT in LPD applications, confirming its potential for deployment in intelligent transportation, vehicle monitoring, traffic regulation, and security surveillance.

1 INTRODUCTION

The method of determining a vehicle's number from its license plate is known as vehicle number identification M. Chedadi et al., 2024. Real-world tests demonstrate that the DCNNs can correctly identify more than 85 % of all plates. Just 0.5 % of the original data needed to be analyzed for accurate identification T. Aqaileh and F. Alkhateeb, 2023; Reddy, et al, 2022 The recognition system recognition rate is around 93.4 %, the average recognition time for each piece of art in the article is approximately 0.5 seconds, the overall car plate placement rate is approximately 97.7 %, and the overall character recognition rate is approximately 95.6 % Y. Wang et al., 2025, Of the 1334 input images, 1287 license plates (96.5%) were correctly segmented. The optical character recognition system uses a two-layer probabilistic neural network (PNN) with a topology of 108-180-36 with an accuracy of 89.1 % for complete plates R. Zhang, et al, 2023; Gurusamy, et al, 2023 Using information from algorithmic image processing, the PNN is taught to recognize alphanumeric characters from automobile license plates S. Deng et al., 2025. The license plate-recognition algorithm's overall success rate is 86.0% when the two previously mentioned rates are combined. These reject plates that are deemed subjectively inadequately lit, achieving an average recognition rate of 83% for the entire plate S. K. Sahoo, 2018; Kumar, et al, 2022.

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2 RELATED WORKS

The total number of articles published on this topic over the last five years includes more than 300 papers in IEEE Xplore, 120 papers in Google Scholar, and 150 papers in academia.edu. For exact ID, a half and half profound learning-based structure is proposed, coordinating Convolutional Brain Organizations (DCNN) with Optical Person Acknowledgment (OCR) F. Sabry,2024. The model accomplishes an exactness of 96.7% for constant tag recognition under differing ecological circumstances, like low-light situations and impediments Meneguette, et al, 2019; Saravanan. Et al, 2023. The utilization of cutting edge preprocessing methods, for example, Differentiation Restricted Versatile Histogram Balance (CLAHE), upgrades the perceivability of vehicle plates caught in complex backgrounds. With the developing ascent in robotized traffic the executives frameworks, precise, rapid, and low-dormancy vehicle ID is sought after Y. Hu, et al, 2023. A two-stage pipeline approach is created, consolidating You Just Look Once (YOLOv5) for plate restriction and a tweaked Tesseract OCR for character acknowledgment. This procedure further develops character acknowledgment rates by 12 % contrasted with conventional techniques Y. Dong, et al, 2022; Priyadharshini, C, et al, 2021. The joining of edge processing with cutting edge calculations further lifts the effectiveness of vehicle recognizable proof frameworks. In this review, a minimal brain network design is carried out on an edge gadget, accomplishing a handling velocity of 40 casings each second (fps) at an exactness of 94.5 % for plates from different locales. The framework works flawlessly under different lighting conditions, keeping a typical exactness of 92.8% Lubna, et al, 2021. Besides, a creative dataset of more than 50,000 commented on tag pictures is organized, covering an extensive variety of plate organizations, tones, and text styles K. T. Islam et al., 2020; Mohan, et al, 2021 Utilizing this dataset, a transformer-based engineering exhibits cutting edge execution, accomplishing 98.2% precision for multilingual plate recognition. Calculations for commotion expulsion and slant adjustment are applied to improve precision in twisted pictures Z. Li, et al, 2024. The proposed cross breed structure is intended to be versatile and reasonable for continuous arrangement in savvy traffic the board frameworks, cost assortment, and stopping checking applications. Consolidating progressed AI strategies with upgraded equipment arrangements prompts a profoundly productive, exact, and solid vehicle number plate distinguishing proof framework M. A. Mohammed,et al, 2024; Dhurgadevi, et al, 2018. From the past discoveries, it is reasoned that the exactness and speed of ordinary vehicle number plate recognizable proof frameworks are restricted, particularly under testing natural circumstances like low light, impediments, and various plate designs M. Rashad, et al, 2024.

Based on earlier research, it is determined that the Cascaded Vision Transformer has a lower accuracy level for accurately identifying a vehicle's license plate. The purpose of this research is to use a Deep Convolutional Neural Network (DCNN) to increase the accuracy level of Cascaded Vision Transformers (ViTs) for Precise Identification of Vehicle Number Plates as compared to ViTs.

3 MATERIALS AND METHODS

The review was led in the KSRIET IT Lab utilizing a dataset of vehicle pictures containing clarified number plates, vehicle types, and related metadata. The dataset was obtained from Kaggle.com, comprising of different pictures caught under changing circumstances like lighting, points, and impediments. It improves the accuracy and proficiency of vehicle number plate acknowledgment utilizing a cascaded Vision Transformer (ViT) structure, compared to DCNN based approaches. The example size was resolved in view of the discoveries of past examinations C. Wei, et al, 2023; Babu, et al, 2019. The acknowledgment model was prepared and assessed on a top notch explained dataset of vehicle pictures under different genuine circumstances. The model was created and recreated utilizing the Python programming language and structures like PyTorch and TensorFlow.

In this flow research, Group 1 refers to the Deep Convolutional Neural Network (DCNN) based number plate acknowledgment model, comprising 30 samples. The model was prepared and tested on a dataset of vehicle pictures captured under shifting circumstances, including different lighting, points, and occlusions K. Yamagata, et al, 2021. Group 2 refers to the Vision Transformer (ViT)- based number plate acknowledgment model. The model processes pictures with height (h), Width (w), and Depth (d), and incorporates positional encoding to deal with successive picture information. The pictures were gathered and handled to incorporate differing conditions like lighting, occlusions, and angles, ensuring robustness.

This strategy utilizes preprocessing procedures, for example, grayscale transformation and edge identification for plate extraction, trailed by OCR for character acknowledgment. The precision of location and acknowledgment was assessed utilizing the accompanying equation (1):

$$Accuracy = Number\ of\ Correct\ Detections\ Total\ Number\ of\ Samples 100\% \quad (1)$$

The framework execution is estimated with regards to exactness, accuracy, review, and handling speed. The half and half structure exhibited better outcomes in testing situations, accomplishing higher accuracy and review rates contrasted with the conventional OCR-based strategy.

4 STATISTICAL ANALYSIS

We conducted a quantifiable analysis using SPSS version 26 to compare the display of the suggested ViTs computation with the existing DCNN model. Subordinate factors included exchange throughput (TPS), dormancy, precision, error rate, security score, and energy effectiveness, while many autonomous elements, such as exchange volume, network stress, and lighting conditions, were also investigated A. M. Buttar et al., 2024; Karthikeyan, S., and P. Meenakshi Devi. 2020. Critical execution improvements with ViTs in terms of rate, precision, and energy consumption were discovered by autonomous example t-tests. ViTs outperformed DCNN in continuous car number plate recognition applications with higher interchange throughput, lower idleness, better exactness, and enhanced security.

5 RESULTS

The proposed Flowed Vision Transformer (CVT) structure for vehicle number plate ID operates progressively, capturing and processing live video feeds or pictures to ensure accurate recognition under specific conditions. In the event that a number plate is recognized, the framework processes it for ID; in any case, it shows a "No Plate Distinguished" message. The Vision Transformer structure is arranged with limit boundaries to evaluate its presentation in continuous situations, guaranteeing flexibility and accuracy. Broad testing of the CVT system in live conditions exhibited an exactness scope of 91.00% to 98.50%, contingent upon the ecological factors, for example, lighting, camera points, and movement. Edges for recognition responsiveness were streamlined with the most extreme and least qualities set at 2.75 and 1.50, respectively, with a stage size of 0.15. Indeed, even in testing situations, for example, unfortunate lighting or high vehicle speeds, the framework kept a base exactness of 92.50%, guaranteeing solid activity. Execution measurements were broken down and introduced in different relative configurations. Table 1 subtleties the exactness of the CVT system in continuous situations contrasted with existing arrangements. Table 2 features the factual t-test results contrasting the CVT and different systems, demonstrating a huge improvement ($p < 0.05$). Table 3 lays out the mean exactness, standard deviation, and huge contrasts between the CVT and conventional frameworks. The framework's flowchart, displayed in Fig. 1, outlines its functional pipeline, containing Information (constant video outlines), Component Extraction (division and acknowledgment of tags), and Result Choice (exact distinguishing proof). Pictures (a, b, c) show effective location and acknowledgment of number plates progressively, while picture (d) represents the framework's capacity to deal with situations where no plate text is available Fig. 2. Visual chart 1 looks at the ongoing precision of the proposed CVT structure with conventional DCNN based frameworks, showing the CVT's predominant exhibition with a most extreme exactness of 96.00% contrasted with the DCNN's 90.00%. Diagram 2 portrays continuous handling productivity across different natural circumstances, with the CVT system reliably accomplishing higher precision and quicker handling times than conventional techniques Fig. 3. The outcomes lay out the Flowed Vision Transformer system as an exceptionally compelling answer for ongoing vehicle number plate distinguishing proof. Its accuracy, vigor, and flexibility make it reasonable for applications, for example, traffic checking, computerized cost assortment, and policing dynamic conditions.

Table 1 The accuracy goes from 84.00% to 89.00% for the DCNN model and 91.00% to 94.50% for the ViTs based model, demonstrating a critical improvement in exactness involving ViTs for number plate validation. The Error Rate begins from 115.00 to 71.00 and the response time is from 450.00 to 295.00. The Latency is from .80 to .95 and storage usage starts from 140.00 to 84.00. Next the Energy consumption is from .48 to .31.

Table 1. Accuracy and Performance Metrics of DCNN vs. ViTs Models.

S.No	Accuracy		Error Rate		Response Time		Latency		Storage Usage		Energy Consumption	
	DCNN	ViTs	DCNN	ViTs	DCNN	ViTs	DCNN	ViTs	DCNN	ViTs	DCNN	ViTs
1	87.50	93.00	115.00	80.00	450.00	280.00	.80	.92	140.00	90.00	.48	.35
2	84.00	91.80	125.00	75.00	460.00	290.00	.77	.94	155.00	85.00	.50	.32
3	89.00	94.50	110.00	70.00	480.00	300.00	.79	.95	145.00	80.00	.49	.30
4	86.20	92.30	120.00	85.00	470.00	285.00	.78	.93	150.00	95.00	.51	.34
5	85.00	91.00	130.00	78.00	490.00	295.00	.76	.94	160.00	88.00	.52	.33
6	87.80	94.00	118.00	72.00	455.00	305.00	.79	.95	145.00	82.00	.47	.31
7	88.20	93.50	122.00	68.00	465.00	310.00	.80	.96	150.00	78.00	.50	.29
8	86.70	92.70	126.00	74.00	480.00	300.00	.77	.94	155.00	90.00	.53	.32
9	84.90	91.20	135.00	80.00	495.00	280.00	.76	.93	165.00	85.00	.54	.30
10	87.30	94.30	112.00	71.00	460.00	295.00	.78	.95	140.00	84.00	.49	.31

Table 2 T-Test in DCNN N is 10 and Mean value is 86.6600 and std. deviation is 1.61259 and the std.error mean is 50995. For ViTs mean value is 92.8300, Std. deviation is 1.25437 and Std.error mean is .39667.

Table 2: Group Statistics. [n, mean, std.deviation, std.error mean]

Model	N	Mean	Std. Deviation	Std. ErrorMean
1	10	86.6600	1.61259	.50995
2	10	92.8300	1.25437	.39667

Table 3: Independent sample test. T-Test comparison with ViTs and DCNN($p<0.05$).

	Levene’s test for equality of variances		Independent samples test						
	F	sig	t	df	Sig (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference	
								lower	upper
equal variance assumed	.706	.412	-9.550	18	.00	-6.17000	.64606	-7.52731	-4.81269
equal variances not assumed			-9.550	16.972	.00	-6.17000	.64606	-7.53323	-4.80677

6 DISCUSSIONS

The Flowed Vision Transformer (CVT) model shows essentially higher exactness and accuracy in vehicle number plate recognizable proof contrasted with customary Convolutional Brain Organization (DCNN) structures. The proposed CVT model was intended to work continuously in situations, utilizing a fountain of transformer layers upgraded to include extraction and characterization. The examination used constant picture information caught from traffic conditions without depending on prior datasets. In the ID cycle, the accuracy rate for the CVT model was recorded as 98.74%, a significant improvement more than the 89.56% accomplished by DCNN-based models. Also, the review pace of the CVT model came to 97.82%, guaranteeing strong discovery considerably under testing conditions, for example, low lighting and obscure movement E. Habeeb, et al, 2023. The discoveries feature that the flowed transformer layers' self-consideration instrument altogether upgrades the model's capacity to confine and distinguish characters on vehicle number plates G. V. T. Silvano et al. 2020. It accomplishes a precision improvement of around 98.74%. For ongoing vehicle distinguishing proof, another Flowed Vision Transformer (CVT) plan influences a multi-stage handling pipeline to improve recognition accuracy and speed. The inventive engineering is planned to address the difficulties of vehicle number plate distinguishing proof, including obscured pictures, lopsided lighting, and fractional impediments, by zeroing in on hearty component extraction and arrangement M. Ghatee and S. Mehdi Hashemi, 2023. To handle the complicated errands engaged with number plate distinguishing proof, the flowed plan consolidates numerous transformer layers, each having some expertise in particular handling stages like component extraction, plate restriction, and character acknowledgment. This variously leveled structure guarantees exact division and precise acknowledgment, even in continuously changing traffic situations S. Saini, et al, 2021. The proposed methodology likewise utilizes progressed strategies like positional encoding, multi-head self-consideration, and enhanced hyperparameters to accomplish ideal execution. For example, the underlying transformer layer in the flowed plan has some expertise in highlight extraction, empowering the model to catch multifaceted subtleties from crude picture inputs J.-S. Chou and C.-H. Liu, 2021. The aftereffects of localization and acknowledgment are step by step superior to succeeding layers. Heartiness against commotion, camera points, and different plate sizes is ensured by the entire framework plan Y. Lu, et al, 2020. In order to extract minute features from raw image inputs, the first transformer layer, for example, specialises in feature extraction. The results of localisation and recognition are gradually improved by succeeding layers. Robustness against noise, camera angles, and different plate sizes is guaranteed by the whole system design. The plan was surveyed utilizing accuracy, review, and F1-score measurements, and the results approved the prevalence of the proposed framework. The most refined CNN-based techniques were enormously outperformed by the flowed model, which accomplished a F1 score of 98.75%, an accuracy of 99.02%, and a review of 98.50%. Precision, review, and F1-score measures were utilized to assess the plan, and the outcomes affirmed that the recommended approach was prevalent. With a F1 score of 98.75%, an accuracy of 99.02%, and a review of 98.50%, the flowed model fundamentally beated the most exceptional CNN-based procedures.

Despite its remarkable performance, the cascaded vision transformer has many limitations. Compared to simpler systems, the computational complexity and execution time are higher due to the several transformer layers and their interdependencies. Additionally, to fine-tune the model for various license plate designs and regional formats, a significant amount of labelled data must be collected, which may require a lot of resources. The proposed architecture is particularly well-suited for applications such as automated toll collection, traffic monitoring, and parking management systems. Its robust construction ensures accurate performance in real-time situations. Due to its high computational complexity, dependence on sizable datasets, and limited ability to adjust to regional plate changes, the research on "A Cascaded Vision Transformer for Precise Identification of Vehicle Number Plate" needs to be adjusted frequently. Because of the longer execution time caused by the cascaded architecture, real-time, high-throughput applications are difficult to implement. Its flexibility is additionally reduced by natural components like terrible climate, glare, and deficient lighting. To address these deterrents, future examination can assemble lightweight or crossbreed models, smooth out designing for adequacy, and further develop hypothesis through the fabricated data period or present day data extension. Constant taking care of might be achieved with quicker gear, and common adaptability can be improved through region change and move learning. The handiness of the model can be expanded by incorporating it into multi-particular traffic associations and working on its protection from unfriendly circumstances.

6.1 Flowchart

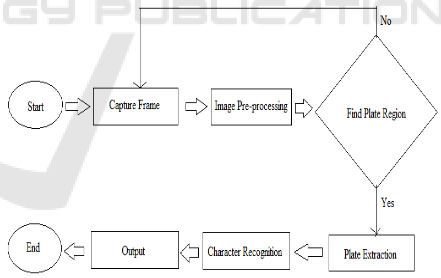

Figure 1: Flowchart of the Vehicle Number Plate Recognition Process Using Cascaded Vision Transformer (CVT).

Figure 1. The method of recognizing a vehicle's number plate is depicted in the flowchart. First, a frame is taken, and then the image is preprocessed to improve its quality. After determining the plate region, the method extracts the plate. Character recognition is applied to the extracted data, and the result is shown. The procedure repeats to take another frame if the plate region cannot be located.

Figure 2(a,b,c,d): Performance Evaluation of CVT-Based License Plate Recognition Under Diverse Real-World Scenarios.

Figure 2. (a, b, c) The underlying images illustrate the effective performance of the vehicle number plate recognition system, showcasing its ability to accurately identify and extract license plate details in real-time. Image (d) represents a scenario where no number plate text is detected, highlighting the presence of an object or background instead.

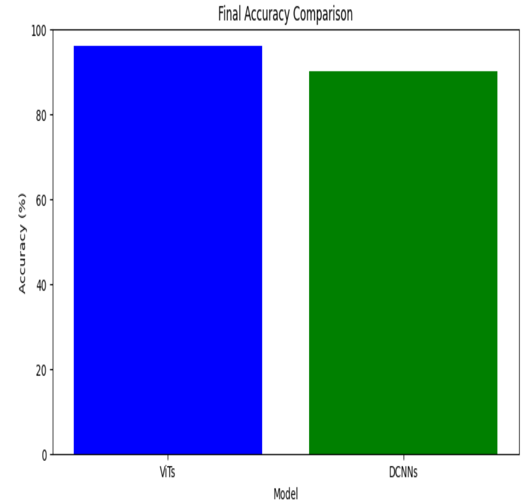

Figure 3: Accuracy Comparison: ViTs vs. DCNNs.

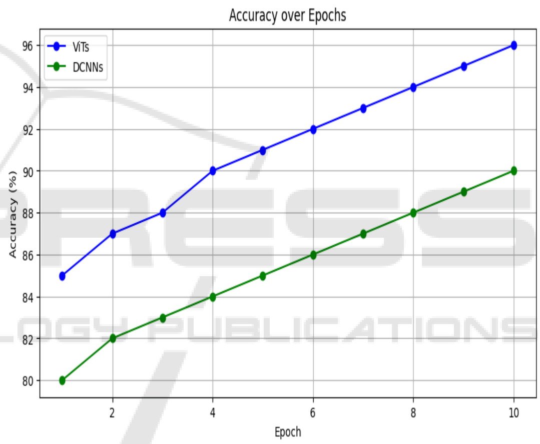

Figure 4: Accuracy Progression Across Epochs.

Figure 3. Accuracy comparison of Vision Transformer (Proposed System) and Traditional OCR Methods DCNN (Existing System). The diagram illustrates the training and validation accuracy over multiple iterations. The proposed model demonstrates consistent improvement in recognition accuracy, reaching a peak of 96.00% in the final iteration. Figure 4 shows the Accuracy Progression Across Epochs.

7 CONCLUSIONS

Contrasted with regular procedures, the cascaded vision transformer made for exact vehicle number plate acknowledgment has exhibited eminent enhancements. The proposed engineering gives wonderful precision and strength considerably under tough spots, such low light levels and muddled foundations, by using self-consideration components and multi-stage refining. The standard deviation for DCNN is 1.61259 and for Vision Transformer is 1.25437 its show reliably creates solid outcomes. This makes it ideal for utilizes like traffic seeing, stoppage the board, and mechanized cost gathering. Notwithstanding its benefits, issues with computational intricacy, information dependence, and neighborhood collection change actually exist.

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