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AI-Enabled Visual Inspection System for Vehicle Fitness Verification

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***Abstract*— An AI-based vehicle fitness testing system is proposed to reduce manual inspection and improve efficiency. It detects visual defects using deep learning models. YOLOv11s and Tesseract offer high speed and accuracy, though Tesseract shows limitations in RC reading. PaddleOCR and DeepSeek OCR improve accuracy but face integration challenges. The system generates automated inspection reports.**

***Keywords*— Vehicle fitness test system, OCR, Object detection.**

I. Introduction

In India, vehicles undergo a fitness test to ensure safety and environmental protection. According to government regulations, a vehicle is required to undergo a mandatory fitness test 15 years after purchase. Thereafter, this test takes place every five years after the first test. This test is of utmost importance as it ensures the safety of both the vehicle owner and those on the road. A single vehicle should be tested on multiple parameters. These parameters can be broadly stated as functional and visual. The visual test includes visual inspection of frame integrity, condition of lighting devices, etc... The functional test checks the functionally important aspects, like brakes. While there is a prescribed pattern for the testing, much of the current process is manual and quite dependent on the judgment of humans. The current manual inspection system leads to inconsistencies, delays, and possible human errors. The lack of automation reduces efficiency and scalability, making it difficult to handle the growing number of vehicles requiring fitness certification. Every day, thousands of vehicles are scanned across the country, burdening the personnel conducting the tests. The huge volume, coupled with monotonous and hard work, often results in fatigue and errors in the results of inspections. Consequently, some unfit vehicles may get through, compromising safety and environmental concerns. The emerging challenge requires an upgraded methodology of testing, automation, and digitalization to ensure more efficiency, consistency, and reliability in assessing vehicle fitness across India.

II. Literature Survey

There is little research trying to automate vehicle inspection in general. A paper proposes an end-to-end framework for fully automated inspection of critical assets by combining autonomous mobile robots (AMRs), multi-modal vision sensors, and AI analytics [1]. The system orchestrates mission planning, autonomous navigation (mapping/localization), and repeatable inspection routes while synchronizing data from RGB/thermal/depth cameras.

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While this is a highly adaptive system, it uses multiple systems that make it difficult for large-scale implementation. In this paper, the researcher suggests an automated fitness test system that incorporates machine learning to minimize subjectivity in Warrant of Fitness (WoF) test results [2]. The results show that using machine learning reduces subjectivity and results in greater consistency. This paper describes an automobile machine vision-based automatic inspection system for surface defects. The authors develop a workable pipeline that normalizes image capturing in the production line, carries out illumination normalization and reflection suppression, and localizes candidate defect areas (e.g. scratches, dents, paint spots) on body panels [3]. However, this system is developed for testing during production.Another paper introduces the use of CNN to do the vehicle fitness test [4]. While all these works are implemented in different ways, a dedicated system for the purpose of vehicle fitness test by comparing various models and an easily navigable interface for the users have yet to be implemented. The work in [8] introduces a vehicle evaluation framework with the comparison of different black box methods.

III. Innovative Content

Develop an AI-based vehicle fitness testing system that automates visual inspection and functional verification tasks by minimizing human intervention and provides consolidated digital test reports. Existing works such as [1] and [9] focus on automated inspection using vision systems and AI, primarily targeting industrial assets and automotive quality control. However, these approaches emphasize defect detection alone and do not integrate document verification or unified reporting. The proposed system extends this by combining visual inspection with OCR-based document validation into a single framework. Research efforts like [2] and [4] address vehicle fitness evaluation using machine learning and convolutional neural networks. While these methods aim to reduce bias in inspection, they lack a complete end-to-end system that includes real-time processing and practical deployment considerations. This work improves upon them by integrating detection, verification, and reporting into a deployable interface. Then, we develop a web interface using Flask that is user-friendly. The web interface also integrates the different modules. A detailed implementation of this system is discussed in the upcoming sections.

IV. Methodology

The AI-based vehicle fitness test system requires the consideration of parameters that must be tested. In this paper, we focus only on visual parameters that can be tested with a camera system. The general process flow of the system is given as a block diagram in Fig 1.

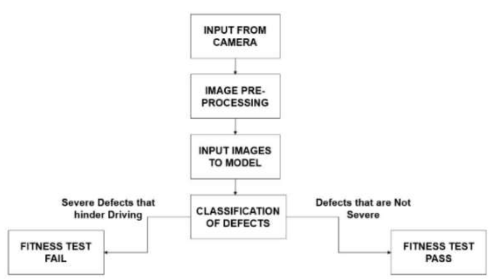


Figure 1. General process flow diagram

A. Selection of visual parameters

From the requirements listed by the Ministry of Road Transport and Highways of India, the parameters for visual inspection were identified. The visual parameters are listed in Table 1 below.

TABLE I. VISUAL INSPECTION PARAMETERS

S. No.	VISUAL INSPECTION	S. No.	VISUAL INSPECTION
1	Inspection of legal documents, insurance and identification of the vehicle	10	Seatbelts (presence, integrity)
2	Steering play	11	Condition of Tyres including spare tyre
3	Chassis / frame integrity	12	Lighting and signaling devices
4	CNG / LPG Safety inspections	13	Oil leakages (engine, transmission)
5	Fuel tank and piping	14	Leaf springs integrity, shock absorbers

6	Exhaust pipe	15	Wind screen, wipers & doors
7	Catalytic converter (mounting, heat shield damages, presence)	16	Horn
8	Engine mountings	17	Availability of Toolbox, First Aid kit, Fire Extinguisher and Warning Triangle
9	Battery (terminals, mounting, etc)	18	Registration plates

B. Dataset collection

The next step is the collection of datasets for training the models. The dataset was collected with the help of platforms like Roboflow Universe, Kaggle, etc. A total of 4106 images were collected for training and 457 images for validation. Apart from the selected parameters, a few severe damages like windscreen damage, etc., were also included in the dataset.

C. Selection of model

The detection and recognition of characters is defined as Optical Character Recognition (OCR). This involves the detection and recognition phase. OCR was used for reading license plates and RC books in this work.

Number Plate Detection
Number plates are recognized to check the vehicle's integrity. Though we do not check the integrity in this paper, the number plate is still detected, and the result will be given as text. This text, if needed, can be used to check the vehicle's integrity. For this purpose, OCR models were chosen and compared. A total of five commonly used OCR models were selected. Tesseract, EasyOCR, TrOCR, YOLO + EasyOCR and PaddleOCR were compared in terms of inference time and accuracy. The results are discussed in section V.A.

RC Book Reading
Similar to license plates, all five models were compared for the purpose of RC book reading. The testing was done with images of RC books collected from online resources. Vital information like chassis number, engine number, etc., was extracted from the RC book using these models. Then the matching rates of the detected text with the actual text were compared for all the models.

Vehicle Defect Detection
Several object detection models have been developed in recent years. Some of them provide the high accuracy required for specific applications. While others provide faster training and inference suitable for certain applications. There is also a wide range of model architectures available today. To mention a few, You Look Only Once (YOLO), Single Shot MultiBox Detector (SSD), Faster R-CNN, etc. Therefore, it is imperative to choose an appropriate model for the AI-based vehicle fitness test system. The works [5,6,7] compare several object detection models in terms of accuracy, inference time, and other important metrics. With the above references, we selected four models to test our dataset. They are YOLO v11s, YOLO v12s, Real-Time Detection Transformer (RT DETR), and RetinaNet. The results of this process can be seen in section V.B.

V. IMPLEMENTATION

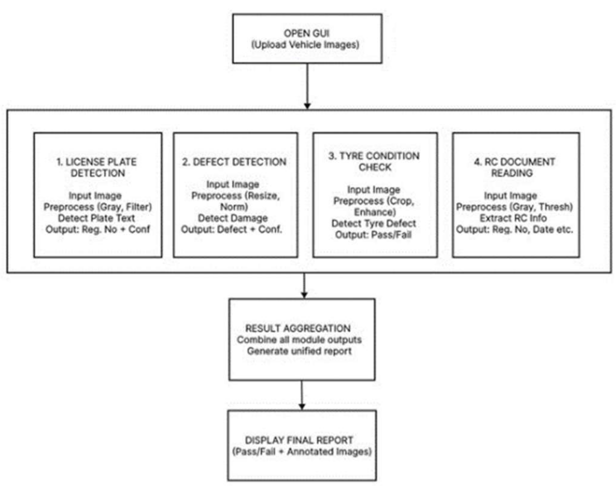


Figure 2. Workflow of the system integrated using Flask

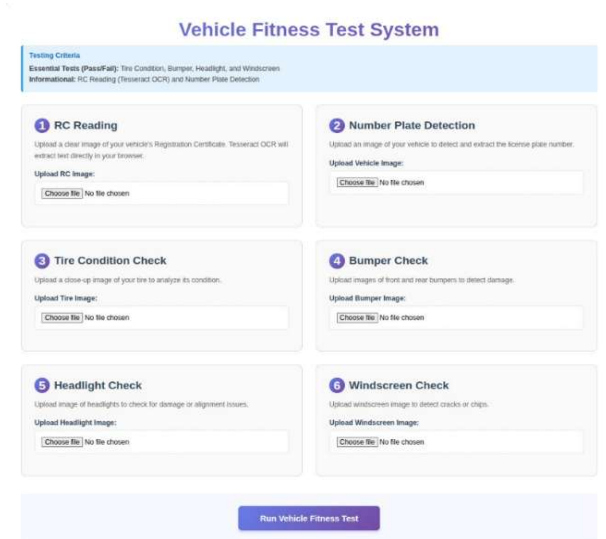
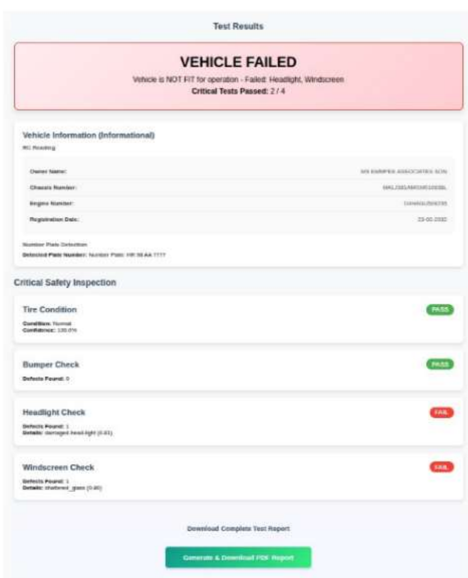
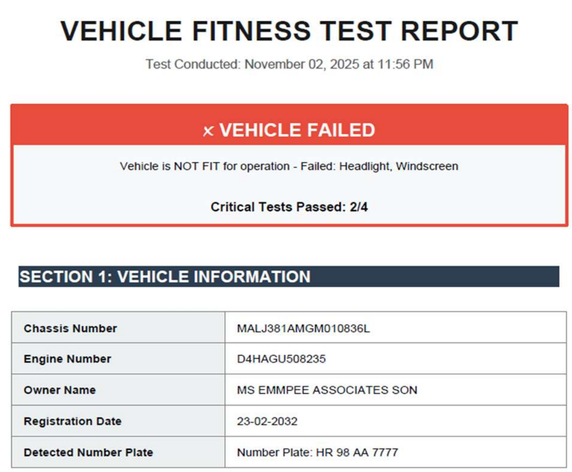


Figure 3. Web interface developed using Flask

Fig. 2 shows the general workflow and is divided into sub-parts that detect different parts of the system. The interface integrates the different modules of the system, like the license plate reading, RC book reading, Defect detection, etc. The interface should be easy to navigate, and the users must be able to operate it without the need for any deep knowledge. Therefore, a web page is created for interfacing the different modules while remaining user-friendly, as shown in Fig 3. The image below, Fig 4, is an example run. The images of the license plate, RC book, parts of the car, and tire were uploaded to the interface. After inference, the results show as in Fig 4. A button to generate and download a detailed report is available on the interface. The users can download the results in a PDF file format for their detailed reference. The following figures show the results in the report.





VEHICLE FITNESS TEST REPORT

Test Conducted: November 02, 2025 at 11:56 PM

× VEHICLE FAILED

Vehicle is NOT FIT for operation - Failed: Headlight, Windscreen

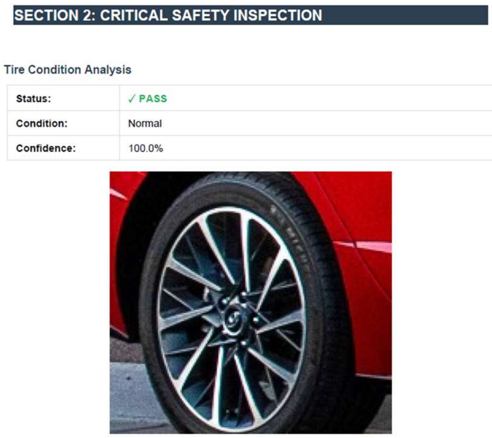
Critical Tests Passed: 2/4

SECTION 1: VEHICLE INFORMATION

Chassis Number	MALJ381AMGM010836L
Engine Number	D4HAGU508235
Owner Name	MS EMMPEE ASSOCIATES SON
Registration Date	23-02-2032
Detected Number Plate	Number Plate: HR 98 AA 7777

Figure 4. Results of the vehicle test after the images are uploaded Figure 5. Part of the report showing the details of the vehicle

Fig 5 presents the part of the report that gives the details of the vehicle. The report shows the results of the OCR model. The images below, Figs 6 and 7, show the next part of the report. It shows the results of the tire analysis and the bumper check. If the tire was found to contain any defects, it would show a bounding box and give the defect in the tire. There are no problems with the bumper, so it passes the check



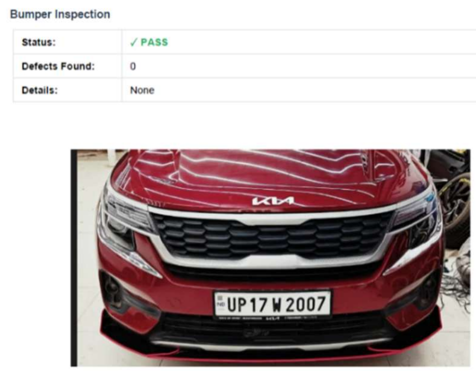
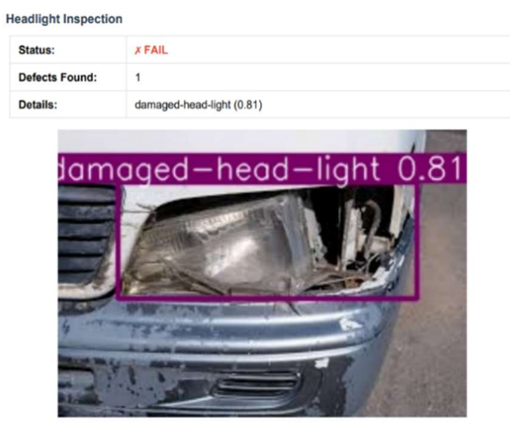


Figure 6. Part of the report showing the results of tire analysis Figure 7. Part of the report showing the result of bumper check

The next part of the report gives the results of the headlight check. Fig 8 illustrates how the defect in the headlight is bounded to highlight the defect. It also shows the failed status of the vehicle. The windscreen is heavily damaged, so the test immediately fails as shown in the above Fig 9.



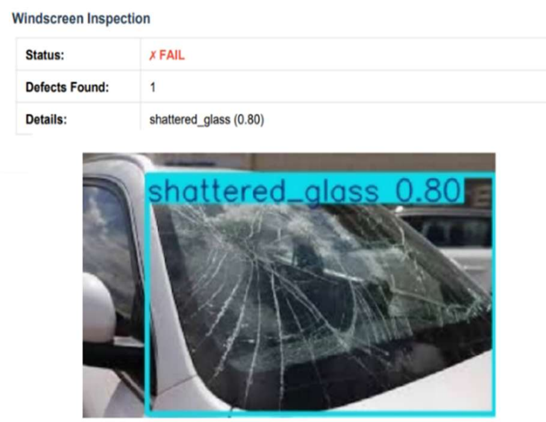


Figure 8. Part of the report showing the results of the headlight check Figure 9. Part of the report showing the results of the windscreen check

VI. Results and Analysis

The following sections show the results obtained through the runs.

A. Comparison of OCR models

The five models, Tesseract, EasyOCR, TrOCR, YOLO + EasyOCR and PaddleOCR were compared. The models were run using pretrained weights, and additional training was not done. The results obtained from the different models for the same input are given in Table II below.

TABLE II. Comparison of OCR Models

MODEL	OUTPUT	TIME (s)	ACCURACY (%)
Tesseract	HR98AA7777	0.09	100
EasyOCR	HR98AA7777	3.25	100
TrOCR	HR98AA7777	1.98	100
YOLO + EasyOCR	HR98AA7777	3.15	100
PaddleOCR	NAOTOEEEEEEIEE	6.11	0

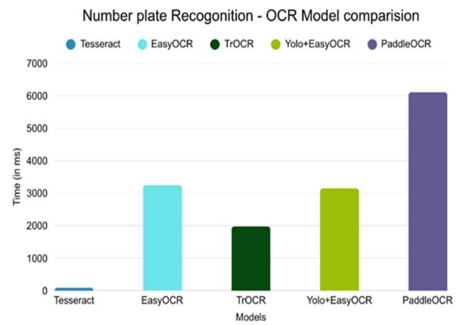


Figure 11. Bar chart comparison of the OCR models

The Fig 11. shows the time taken for different tasks as a bar chart. From the chart, it can be identified that Tesseract takes the minimum time. Therefore, Tesseract was chosen for license plate recognition. Fig 12 shows how the Tesseract model is less accurate when it is used for RC reading. The test results give a less accurate registration number in the given example. Similarly, for different images, the results are inconsistent. This prompted the use of different models for the purpose of RC reading, like PaddleOCR and DeepSeek OCR, for a given image, as shown in Fig 13. Table III below gives the time taken for inference by PaddleOCR and DeepSeek OCR to run for RC reading.

TABLE III. RESULTS OF PADDLEOCR AND DEEPSEEK OCR

MODEL	TIME (s)	ACCURACY (%)
PaddleOCR	2.5	100
DeepSeek OCR	1.83	100

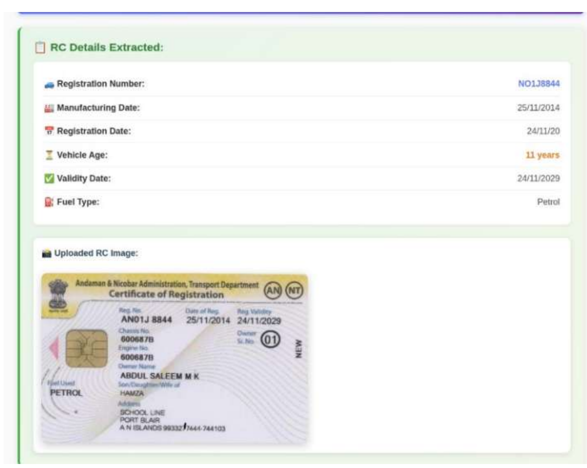


Figure 12. Failed results of RC reading using Tesseract

Figure 13. RC reading result using Paddle OCR

B. Comparison of object detection models

All the models were run online using an external cloud GPU. Training of each model was carried out using the prepared dataset. 50 epochs were selected for all four models. RetinaNet was eliminated early as the loss was high, and the improvement stagnated despite changing the epochs and learning rate. Two of the formulae used to compare models are as follows:

True Positive (TP): A predicted bounding box that correctly matches a ground truth box with an IoU ≥ threshold (usually 0.5).

False Positive (FP): A predicted bounding box that does not correspond to any ground truth (IoU < threshold).

False Negative (FN): A ground truth object that the model failed to detect.

Precision (P)

$$P = \frac{TP}{TP + FP} \quad (1)$$

Recall (R)

$$R = \frac{TP}{TP + FN} \quad (2)$$

Equation (1) represents how many predicted detections are correct, while (2) represents how many true objects were successfully detected.

TABLE IV. COMPARISON OF OBJECT DETECTION MODELS

METRIC	YOLOV10	YOLOV11S	YOLOV12	RT DETR
MPA 50	0.467	0.6017	0.5958	0.6334
mPA 50-95	0.468	0.4239	0.4291	0.4687
Precision	0.887	0.5965	0.5658	0.6540
Recall	0.863	0.6101	0.5910	0.6358
Training / Inference Time & Efficiency	Efficient (Low Latency)	4217 S (Training)	5943.6 S (Training)	15717.6 S (Training)

VII. CONCLUSION

The AI-based vehicle fitness test system developed in this paper has high potential to be implemented in many official testing locations, since the system helps reduce the load on the workers. The analysis of different models shows that for a fast and accurate prediction of defects, YOLO v11s is the best-suited model. For optical character recognition, the comparison results present Tesseract as the fastest model. However, the developed system can be improved further. Currently, the input of images is done manually by the operator in the developed system. This process can be fully automated. Further, more visual inspection parameters can be trained to allow a complete inspection. Additionally, functional inspection can also be automated with the help of AI using sensor data. These limitations set the goal for the improvement of the AI-based vehicle test system.

REFERENCES

[1] Sanchez-Cubillo, J., Del Ser, J., & Martin, J. L. (2024). Toward Fully Automated Inspection Of Critical Assets Supported By Autonomous Mobile Robots, Vision Sensors, And Artificial Intelligence. Sensors, 24(12), 3721.

[2] Geethmal, D. G. T. L., & Sapraz, M. (2024). Designing An Automated Vehicle Fitness Evaluation System By Integrating Machine Learning To Achieve Unbiased Results In Warrant Of Fitness Assessments. In Transformative Applied Research In Computing, Engineering, Science And Technology (Pp. 55-62).

[3] Zhou, Q., Chen, R., Huang, B., Liu, C., Yu, J., & Yu, X. (2019). An Automatic Surface Defect Inspection System For Automobiles Using Machine Vision Methods. Sensors, 19(3), 644

[4] Guharoy, R., Deshkar, D., Raskar, S., Alimkar, N., Dalvi, P., & Foujdar, D. (2024, October). Evaluation Of Vehicle Fitness Using Convolutional Neural Networks. In 2024 Ieee International Conference On Computer Vision And Machine Intelligence (Cvmi) (Pp. 1-5).

[5] Tian, J., Jin, Q., Wang, Y., Yang, J., Zhang, S., & Sun, D. (2024). Performance analysis of deep learning-based object detection algorithms on COCO benchmark: a comparative study. Journal of Engineering and Applied Science, 71(1), 76.

[6] Jabir, B., Falih, N., & Rahmani, K. (2021). Accuracy and efficiency comparison of object detection open-source models. International Journal of Online & Biomedical Engineering, 17(5).

[7] Sanchez, S. A., Romero, H. J., & Morales, A. D. (2020, May). A review: Comparison of performance metrics of pretrained models for object detection using the TensorFlow framework. In IOP conference series: materials science and engineering (Vol. 844, No. 1, p. 012024). IOP Publishing.

[8] Alwadi, M., Chetty, G., & Yamin, M. (2023). A framework for vehicle quality evaluation based on interpretable machine learning. International Journal of Information Technology, 15(1), 129-136.

[9] Rio-Torto, I., Campanico, A. T., Pinho, P., Filipe, V., & Teixeira, L. F. (2022). Hybrid Quality Inspection for the Automotive Industry: Replacing the Paper-Based Conformity List through Semi-Supervised Object Detection and Simulated Data. Applied Sciences, 12(11), 5687.

[10] Nascimento, A. M., Vismari, L. F., Molina, C. B. S. T., Cugnasca, P. S., Camargo, J. B., de Almeida, J. R., ... & Hata, A. Y. (2019). A systematic literature review about the impact of artificial intelligence on autonomous vehicle safety. IEEE Transactions on Intelligent Transportation Systems, 21(12), 4928-4946.