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Deep Learning based Tire Wear Defective Analysis

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ABSTRACT: This study introduces an automated tire defect detection system employing the YOLOv5s deep learning architecture. Tire defects such as cracks, punctures, and worn-out treads present major safety concerns and require prompt identification. Traditional manual inspections are inefficient and error-prone. To address this, a deep learning model was trained on a labeled dataset categorized into "Good" and "Defective" tires using YOLO annotation format. The YOLOv5s model was selected for its lightweight design and real-time performance capabilities. Training utilized transfer learning in PyTorch to accelerate convergence and enhance accuracy. The model accurately localizes and classifies defects with bounding boxes and confidence scores. A responsive web interface was developed using the Flask framework to allow users to upload tire images and view defect predictions. The system includes user login, registration, and prediction pages for interactive use. The approach demonstrates strong performance, scalability, and applicability in vehicle maintenance and safety domains

KEYWORDS: YOLOv5s, tire defect detection, deep learning, object detection, transfer learning, real-time inference.

I. INTRODUCTION

In the modern era, the reliance on road transportation has increased significantly, necessitating enhanced vehicular safety measures. Tires, serving as the only contact point between a vehicle and the road, play a pivotal role in ensuring both operational performance and safety. However, tire inspection is often neglected or performed manually, introducing inconsistencies, inefficiencies, and the potential for human error, particularly in contexts involving high service volumes or extensive vehicle fleets[1]. This underscores the demand for an automated, intelligent tire condition assessment system.

Recent advances in machine learning (ML), particularly in deep learning and computer vision, have demonstrated considerable potential in solving complex image analysis problems. Object detection—a core domain in computer vision—enables models to not only recognize objects within an image but also accurately localize them. The You Only Look Once (YOLO) series of models, especially YOLOv5, offer an optimal trade-off between detection accuracy and inference speed, even in computationally constrained environments.

This study presents a tire defect detection framework leveraging the YOLOv5s (small) architecture, selected for its computational efficiency and capability to perform real-time inference. The model's architecture, comprising a backbone for feature extraction, a neck for feature aggregation, and a head for final predictions, is particularly well-suited for deployment in scenarios requiring lightweight yet robust solutions. The system is trained on a custom-annotated image dataset with two primary classes: 'Good' and 'Defective' tires. Defects include visible anomalies such as punctures, cracks, and tread wear. Each image is annotated in YOLO format, enabling the model to learn spatial and contextual representations of tire conditions.

Training is conducted using the PyTorch framework, incorporating transfer learning via pretrained weights on the COCO dataset. This approach accelerates convergence and enhances the model's generalization capacity. Fine-tuning on the domain-specific dataset ensures accurate recognition of defect-specific features[2]. Model evaluation metrics confirm the capability of YOLOv5s to perform high-precision, real-time detection.

To facilitate user interaction, a responsive web application was developed using the Flask micro web framework. This interface enables users to upload tire images and receive real-time predictions. Detected regions are visualized using bounding boxes, color-coded by classification (e.g., green for 'Good', red for 'Defective') and annotated with corresponding confidence scores. The web application also features user authentication (login and registration) and





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informational pages such as "About", "Contact", and a "Prediction" interface, ensuring accessibility and engagement for end users.

Unlike traditional classification approaches that merely provide a global label, the object detection capabilities of YOLOv5s enable the system to analyze multiple objects within an image, delivering localized and interpretable outputs. This feature is critical for practical deployment in real-world scenarios, where multiple tires may appear in a single frame or where defects may be subtle and localized. The proposed system exemplifies the integration of open-source ML frameworks, community-driven tools, and systematic software engineering practices. YOLOv5, maintained by Ultralytics, offers modular, extensible components ideal for domain-specific applications such as tire defect detection [3]. The project pipeline—from data collection and preprocessing through model training and evaluation to web-based deployment—reflects a rigorous and structured approach. Each stage contributes to enhancing the system's reliability, usability, and scalability.



Fig-:1. Proposed Architecture

In this **Fig 1** the Proposed Architecture says that a comprehensive, AI-enabled vehicle safety application that combines state-of-the-art object detection with intuitive web-based interaction. The implementation of a Flask-powered web interface ensures widespread accessibility and user-friendliness, while the underlying deep learning model provides robust and real-time diagnostic capability. The system offers a scalable solution for tire condition monitoring and has potential for extension to additional vehicle components or integration into broader intelligent transport and maintenance ecosystems.

II. RELATED WORK

Extant scholarship underscores the pivotal role of automated tire defect detection systems in bolstering vehicular safety and ensuring operational reliability. Conventional methodologies have largely relied upon manual inspection protocols or classical image processing techniques aimed at identifying surface-level anomalies—such as cracks, bulges, cuts, and irregular tread wear patterns. These approaches typically necessitate the extraction of handcrafted features from grayscale or color imagery, followed by classification using traditional machine learning algorithms including Support Vector Machines (SVMs), k-Nearest Neighbours (k-NN), and Random Forests. While such methods have demonstrated efficacy in controlled experimental settings, their performance often deteriorates under real-world conditions, where challenges such as inconsistent illumination, occlusions, dirt, and diverse tire geometries introduce significant variability. This lack of robustness and limited capacity for generalization has catalyzed a transition toward more adaptive, data-driven paradigms [4].

Early-stage tire defect detection systems, primarily grounded in low-level vision algorithms—such as edge detection, contour analysis, and texture segmentation—sought to delineate anomalous surface characteristics. Manually engineered features, such as tread depth fluctuations, radial discontinuities, and shape asymmetries, were extracted and subsequently input into classifiers. However, these systems were inherently constrained by their reliance on domain-specific thresholds and their susceptibility to environmental perturbations.





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The advent of deep learning, particularly the You Only Look Once (YOLO) object detection framework, has precipitated a paradigm shift in the field of automated visual inspection. YOLOv5s—a lightweight, real-time variant— affords efficient localization and classification of tire defects directly from raw image data. Unlike traditional pipelines, YOLOv5s obviates the need for manual feature engineering by autonomously learning hierarchical spatial features through deep convolutional layers. Moreover, the application of transfer learning, coupled with advanced data augmentation techniques (e.g., mosaic augmentation, random scaling, affine transformations), enhances the model's resilience to intra-class variability, environmental noise, and imbalanced datasets. Consequently, YOLOv5s exhibits superior generalizability and robustness, rendering it an optimal choice for deployment in heterogeneous operational environments characterized by high throughput and minimal tolerance for diagnostic error[5].

Numerous studies have harnessed Convolutional Neural Network (CNN) architectures for related domains in the automotive sector, including vehicle part inspection, road surface anomaly detection, and industrial quality control. For instance, Zhang et al. (2021) employed a CNN-based model for real-time detection of road surface defects, achieving classification accuracies surpassing 92%, thereby illustrating the potential of deep learning frameworks in high-precision visual diagnostics. Parallel efforts have extended these techniques to the automotive context by analyzing surface wear, material fatigue, and pattern irregularities in components such as tires and brake discs[6]. These investigations collectively reinforce the applicability of CNNs in discerning nuanced defect morphologies in vehicular systems.

Advancements in this space have increasingly incorporated hybrid models that amalgamate CNNs with temporal architectures, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, particularly in scenarios involving video-based inspection systems. Such models are adept at capturing temporal defect evolution across multiple frames—useful in dynamic surveillance environments or conveyor-based tire inspection setups—thereby enhancing detection accuracy and continuity in operational workflows[7]. These hybrid approaches enable the extraction of spatiotemporal features, such as progressive tread deterioration and intermittent radial anomalies, which static image classifiers may fail to discern.

A significant bottleneck hindering broader progress in tire defect detection is the limited availability of high-resolution, domain-specific, and expertly annotated image datasets. Most existing datasets are either proprietary, narrowly scoped, or oriented toward generalized object detection, lacking fine-grained annotations that specify defect typologies such as bulges, cracks, punctures, or asymmetric wear. Consequently, many studies rely on controlled data acquisition environments, often constraining the external validity and scalability of the trained models. The creation and public dissemination of diverse, demographically representative tire defect datasets remain a pressing requirement for fostering generalizable solutions.

Concurrently, the integration of interpretable artificial intelligence (AI) frameworks—such as Gradient-weighted Class Activation Mapping (Grad-CAM) and Shapley Additive explanations (SHAP)—has emerged as a pivotal advancement in enhancing model transparency and accountability. These methods enable visualization of the specific tire regions that contribute most significantly to the model's classification output, thereby elucidating its decision-making rationale. Such interpretability not only facilitates debugging and model refinement but also engenders greater trust among automotive engineers and end-users, aligning with ethical AI deployment standards in safety-critical domains [8].

III. IMPLEMENTATION

The implementation of the proposed vehicle tire defect detection system begins with the acquisition of a highresolution input image, which serves as the basis for subsequent computational processing. These images are captured using conventional digital imaging equipment, including surveillance cameras, mobile phones, or dedicated visual inspection systems installed in automotive service centers or inspection booths.

This **Fig 2** should encompass the visible surface of the vehicle tire, particularly focusing on the tread and sidewall regions, as these areas are most susceptible to structural wear and damage. The goal of this initial phase is to ensure that the acquired image accurately represents the tire's condition, providing a suitable foundation for the detection of potential defects [9].





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Fig:2. Flow of proposed model

Following image acquisition, a preprocessing stage is conducted to standardize and optimize the input data for compatibility with the YOLOv5s deep learning model. Preprocessing involves resizing the image to a fixed dimension expected by the model, typically 640×640 pixels, to maintain consistency in input dimensions. Additionally, the image undergoes normalization, wherein pixel values are scaled to a range between 0 and 1, thus facilitating more stable training and inference performance. The image is then converted into a format appropriate for model ingestion, often as tensors through PyTorch's preprocessing utilities [10]. This step ensures that the model receives input in a manner conducive to efficient computation and effective feature extraction.

Once the image is pre-processed, it is forwarded to the core of the detection system: the YOLOv5s (You Only Look Once version 5 - small) object detection model. YOLOv5s is selected for its lightweight architecture and high-speed inference capabilities, making it suitable for real-time deployment. The model processes the input image by dividing it into a grid and simultaneously predicting bounding boxes and class probabilities for each cell. Each bounding box corresponds to a detected object—here, a tire region categorized as either 'Good' or 'Defected.' YOLOv5s employs a CSPDarknet backbone, PANet neck, and YOLO detection head to extract multilevel spatial features that distinguish between healthy tire surfaces and various defect types, including cracks, bulges, punctures, and abnormal tread wear. The raw predictions produced by YOLOv5s require refinement to improve interpretability and eliminate redundant or low-confidence outputs. This is achieved through the application of non-maximum suppression (NMS), a technique that filters overlapping bounding boxes based on intersection-over-union (IoU) and confidence score thresholds. Only the bounding box with the highest confidence score is retained among overlapping candidates, thereby enhancing the clarity and reliability of the detection. A minimum confidence threshold (e.g., 0.5) is also applied to discard uncertain predictions. The refined output comprises precise bounding boxes that localize defects, accompanied by class labels and prediction confidence values.

Subsequently, the final detection results are visualized using annotated overlays on the original input image. Bounding boxes are color-coded for immediate visual interpretation: red indicates a detected defect, while green denotes a healthy region. These visual cues enhance the usability of the system by enabling quick diagnostic decisions without requiring domain expertise. Additionally, each bounding box is labeled with the associated class and confidence percentage, providing further context for decision-making [11]. This visual output forms the primary interface through which users interact with and evaluate the system's performance.

To facilitate user interaction, the detection pipeline is embedded within a graphical user interface (GUI) developed using Python's Tkinter library. The GUI allows users to upload tire images from their local storage, initiate the detection process, and view the annotated output within a single window. The interface is designed for simplicity and accessibility, making it usable by non-technical individuals such as mechanics, fleet managers, and inspection personnel. The GUI provides buttons for image selection and processing, and dynamically updates to display results





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without requiring users to interact with the underlying codebase. This design enhances the system's practicality in realworld automotive service environments.

Finally, the system architecture is designed to support scalability and integration with remote or distributed platforms. Although initially implemented as a desktop application, the system can be deployed on cloud-based infrastructures through frameworks such as Flask or Django, allowing for web-based interaction. Users can upload tire images via a browser interface and receive predictions remotely, enabling deployment across multiple service centers or vehicle fleets. Furthermore, the modular design supports future enhancements such as integration with mobile apps, continuous video stream processing, and expansion to detect other automotive component defects [12]. In essence, the implementation leverages deep learning and user-centered design to deliver an efficient, scalable, and accurate tire

Ref	Algorithm	Accuracy	
[13]	Deep Convolutional Neural Networks (CNN)	85% to 90%	
[14]	Hybrid Deep Learning (CNN + Traditional ML)	80% to 88%	
[15]	Image Processing + CNN	75% to 85%	
[16]	Lightweight CNN (e.g., MobileNet variants)	78% to 86%	
[17]	Real-Time CNN	70% to 80%	
[18]	ML Regression Models (SVM, Random Forest)	65% to 75%	
[19]	Time-Series Deep Learning (LSTM, CNN)	68% to 78%	
[20]	Deep Convolutional Networks (CNN)	85% to 92%	

Table 1.	Comparision	summary o	of different	models used

IV. METHODOLOGY

The initial phase of the methodology entails the collection of a comprehensive and diverse dataset of vehicle tire images encompassing both non-defective (good) and defective samples. Each image is annotated using the YOLO (You Only Look Once) object detection format, which includes precise bounding box coordinates and corresponding class labels for defects such as cracks, punctures, and tread wear. This manual annotation process, conducted using specialized labeling tools, ensures a high degree of accuracy and consistency in the training data. The primary objective of this step is to enable the detection model to accurately identify both the presence and spatial location of various tire defects. These labeled datasets serve as the essential foundation for training the object detection algorithm.

For the object detection task, the YOLOv5s model was selected due to its real-time inference capability and low computational requirements. YOLOv5s, a lightweight convolutional neural network architecture, is specifically designed for rapid object detection in resource-constrained environments. The Training process utilizes transfer learning, wherein pre-trained weights are adapted to the custom dataset of tire images. Model training was performed





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using the PyTorch framework, incorporating data augmentation techniques to enhance generalizability and performance under diverse imaging conditions. The trained model's performance was evaluated based on standard metrics such as precision, recall, and mean Average Precision (mAP). Upon successful training and validation, the model was exported and integrated into the application framework for deployment.

The system interface was developed using the Flask micro-framework to facilitate user interaction through a web-based environment. Flask manages HTTP request routing, session control, and integration with HTML templates via Python back-end scripts. Specific routes were implemented to handle functionalities including user authentication, image upload, and defect detection processing. A secure, session-based login system was established using password hashing to protect user credentials. The template rendering engine in Flask enables dynamic webpage generation, offering a responsive and intuitive user experience. This design ensures seamless interaction between the user and the detection system.

Upon successful login, users are granted access to an image upload feature integrated within the web interface. The uploaded tire image is stored in a designated server directory and subsequently passed to the YOLOv5s model for inference. The trained model processes the input and generates detection outputs consisting of bounding box coordinates, class labels, and associated confidence scores. These detections are then visualized by overlaying bounding boxes on the original image using the Python Imaging Library (PIL). Each defect detection is annotated with a label and a confidence value, color-coded for visual clarity—facilitating easy identification of defects.

Following the inference process, the annotated image is saved and displayed back to the user via the web interface. Tires classified as "Good" are highlighted in green, while "Defected" tires are marked in red, accompanied by corresponding confidence levels. This annotated feedback is designed to offer immediate, interpretable results, enabling users to make informed decisions based on visual evidence. The interactive visualization significantly enhances the system's usability, particularly for non-technical stakeholders, by simplifying the interpretation of machine-generated results.

In summary, the methodology integrates deep learning and web technologies to deliver a robust, real-time tire defect detection system. The use of YOLOv5s ensures high-speed inference, while the Flask-based web interface enables accessible and secure user interaction. This comprehensive approach, combining machine learning, GUI design, and database integration, demonstrates the practical implementation of intelligent systems in the automotive domain. The solution lays a scalable groundwork for future advancements, including mobile deployment, multi-angle detection, or integration with IoT-enabled diagnostic platforms.



V. RESULTS

Fig: 3. Precision-Confidence Curve

In Fig 3 Precision-Confidence Curve provides a visual representation of how the model's precision changes with varying levels of confidence thresholds for each class. The "defected" class shows consistently high precision even at





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lower confidence levels, which indicates the model's strong ability to correctly classify defective tires with minimal false positives. In comparison, the precision for the "good" class increases more gradually, suggesting slightly lower early confidence in classification. The bold blue line representing all classes illustrates that the model achieves its peak overall precision of 1.00 at a confidence threshold of 0.845. This curve is useful for selecting an appropriate confidence threshold that balances accuracy and prediction certainty.



Fig: 4. Precision-Recall Curve

Fig. 4 shows Precision-Recall Curve demonstrates the relationship between precision and recall, two key performance metrics, across different confidence thresholds. The "defected" class achieves a high precision of 0.995, highlighting the model's ability to detect true positives with minimal error. Similarly, the "good" class exhibits a precision of 0.961, indicating strong but slightly lesser classification performance. The overall mean Average Precision (mAP) at 0.5 is calculated to be 0.978, which reflects the model's high-level detection effectiveness across all categories.



Fig:5. Recall-Confidence Curve

The **Fig 5** shows Recall-Confidence Curve illustrates how the recall metric behaves as the model's confidence threshold increases. The curve reveals that the model maintains high recall values—especially for the "good" class—across a broad range of thresholds. This suggests that the model reliably identifies most positive instances, particularly in images of tires without defects. In contrast, the recall for the "defected" class decreases more quickly with increasing thresholds, indicating that some defective cases may go undetected if the confidence requirement is too high. Overall, the model demonstrates strong recall performance, particularly at lower thresholds, supporting its ability to detect true positives in real-world applications.





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<figure>

Fig:6. Results of Tire wear Detected

The training process is evaluated using various loss components and performance metrics visualized over 100 epochs. The training losses—box loss, objectness loss, and classification loss—show a consistent downward trend, signifying effective learning and model convergence. Validation losses similarly decline, closely following the training losses, which indicates that the model generalizes well without significant overfitting. Additionally, metrics such as precision, recall, and mAP@0.5 rise steadily throughout the training process. In **Fig.6** these plots collectively affirm that the training process was stable, and the model attained a high level of performance and reliability by the end of training.



Fig:7. Detection of Tire wear

Fig. 7 presents the interface presented in the image illustrates a web-based tire defect detection system. Users can upload an image of a vehicle tire, which is then processed by a trained deep learning model to determine its condition. The output section displays the analyzed image with a bounding box indicating the predicted class—here labeled as "Defected" with a confidence score of 0.65—visibly overlaid on the image. Additionally, the interface provides options to view the confusion matrix and ROC curve, enabling users to assess the model's classification performance and diagnostic accuracy.



Fig:8 .Confusion Matrix of the Result

Fig. 8 presents the confusion matrix of the tire defect detection model's classification results. This matrix visually summarizes the model's performance by showing the number of true positive, true negative, false positive, and false negative predictions. It helps users quickly understand how accurately the model distinguishes between defected and





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non-defected tires, highlighting areas where the model excels or may require improvement. The confusion matrix is a critical tool for evaluating the effectiveness and reliability of the deep learning system in practical applications.

VI. CONCLUSION

This project successfully demonstrated the development of an intelligent, real-time tire defect detection system utilizing the YOLOv5s deep learning architecture. The model was trained on a custom-labeled dataset, enabling it to accurately identify various tire anomalies such as cracks, bulges, punctures, and tread wear. Owing to its lightweight design and high inference speed, YOLOv5s proved suitable for deployment in environments with limited computational resources. The training and validation phases affirmed the model's high precision and recall, indicating robust detection capability. A user-friendly graphical interface was developed using Tkinter to facilitate seamless interaction with the system. Users can upload tire images and receive instant predictions, which are visually rendered with bounding boxes and confidence scores for enhanced interpretability. This real-time feedback mechanism supports timely decision-making in safety-critical scenarios. The system thus bridges the gap between advanced computer vision models and practical usability in automotive contexts.

The proposed system holds significant potential for application in automotive workshops, production line inspections, and transportation safety audits. By automating the defect identification process, it minimizes human error, enhances diagnostic accuracy, and improves operational efficiency. Furthermore, the modular architecture of the solution allows for future enhancements such as mobile integration, multi-angle analysis, and broader defect classification. Overall, this work exemplifies how artificial intelligence can be effectively harnessed to improve road safety and preventive vehicle maintenance.

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