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Automated Vehicle Damage Detection and Cost Estimator for Insurance Companies

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Abstract: Using state-of-the-art deep learning algorithms, the "Automated Vehicle Damage Detection & Cost Estimator for Insurance Companies" project seeks to transform the vehicle insurance industry by automating the damage assessment process. This AI-powered system uses YOLOv5, one of the most sophisticated object identification models available, to effectively analyse and evaluate vehicle damage, including that of two-wheelers and four-wheelers. The model can precisely identify, categorize, and assess various forms of damage, such as scratches, dents, cracks, and shattered pieces, because it has been thoroughly trained on a vast dataset of car damages. This high degree of accuracy lowers the possibility of errors in computations and false claims by guaranteeing that even small damages are accurately identified. Insurance firms may improve the speed of their claims processing, reduce human error, and produce accurate repair cost estimates based on real-time damage analysis by putting deep learning and computer vision technology into practice. By automating the evaluation process, the system will do away with the necessity for manual inspections, which are frequently laborious, arbitrary, and prone to errors. Additionally, the system would forecast repair costs based on variables like labor prices, spare parts, and vehicle depreciation by integrating repair cost estimating models. This will enable insurance companies to give equitable and transparent claim settlements. The entire insurance process will be greatly streamlined by this cutting-edge technology, which will not only speed up damage assessment but also result in quicker claim settlements and higher customer satisfaction. Owners of vehicles may now upload photos using a mobile application, and the system will automatically assess the damage and provide an immediate cost estimate, eliminating the need for them to wait days for damage assessment. By guaranteeing impartial, data-driven, and equitable claim handling, this automation-driven strategy would not only lower operating expenses for insurance companies but also foster confidence between policyholders and insurers.

Keywords: Vehicle Damage Assessment , Cost Estimation , You Only Look Once version 5 (YOLOv5), Insurance Automation, Deep Learning (DL), Object Detection, AI-Powered Claims Processing , Repair Cost Prediction),Computer Vision (CV), Insurance Fraud Prevention, Real-Time Assessment, Machine Learning (ML), Smart Claims Management .

I. INTRODUCTION

The insurance industry has been using digital technologies more and more in recent years to increase operational efficiency. The procedure for assessing vehicle damage and estimating costs, which presently depends on manual inspection, is one crucial area that needs improvement. Inconsistencies in claim evaluations result from this conventional method's subjectivity, time commitment, and human mistake potential. Inaccurate damage assessments, lengthy claim processing times, and perhaps fraudulent claims are some of the difficulties insurance firms confront. Artificial intelligence (AI) and deep learning-based models, especially object identification methods, provide a possible remedy. The Iterative Closest Point algorithm and optical radar are two examples of cutting-edge computer vision technologies that have been shown to have promise for assessing vehicle damage [1]. YOLO (You Only Look Once) is a well-known deep learning model for its quickness and precision in identifying objects in pictures and videos [2]. Transformer prediction heads and multi-class damage detection are two examples of YOLOv5 enhancements that have greatly increased performance and are appropriate for real-time vehicle damage assessment [2,3].With an emphasis on two- and four-wheelers, this research suggests an AI-driven system that analyses vehicle damage using YOLOv5. The technology uses cost estimating algorithms to precisely forecast repair costs and automate the damage diagnosis procedure. The system seeks to improve damage detection accuracy, decrease claim processing time, and increase customer satisfaction by utilizing deep learning and automated assessment [4,5]. The viability of AI-based damage identification and repair cost estimating techniques for insurance applications has been confirmed by a number of studies that have confirmed its efficacy [4,5]. The precision of the models, dataset quality, and system integration still present difficulties despite the benefits.

Issues like illumination fluctuations, various forms of damage, and occlusions in vehicle photos have been brought to light by researchers [6,7]. Vehicle evaluation tasks have been greatly improved by advancements in feature pyramid networks (FPNs) and real-time detection models in order to overcome these constraints [3]. Furthermore, automated cost estimating techniques in conjunction with deep learning models enhance the dependability of AI-powered insurance solutions [6].By creating a reliable AI-based system for automotive damage detection and cost prediction, this project seeks to close the gap between manual and automated damage assessment. The system intends to improve the speed, accuracy, and transparency of processing insurance claims by combining deep learning, computer vision, and insurance domain knowledge. Hybrid AI models that combine deep learning and machine learning-based regression techniques will be used to improve the accuracy of cost estimation [5,6]. By taking into account variables including regional repair costs, labor costs, spare part availability, and vehicle depreciation rates, this method allows for a more thorough and adaptable damage-to-cost mapping [7].

II. LITERATURE REVIEW

There has been a lot of recent research on the application of deep learning and computer vision to the identification of automobile damage and insurance automation. The key strategies and difficulties in this field have been examined in a number of research.

Using the Iterative Closest Point (ICP) approach to increase collision analysis accuracy, Lin and Chen [1] presented an optical radar-based method for evaluating vehicle damage. This technique uses accurate point cloud data to improve damage estimation. In order to meet the need for improved localization and classification of vehicle damages, Roy and Bhaduri [2] suggested an enhanced YOLOv5 model with a Transformer Prediction Head to improve damage detection accuracy. Similarly, Liu et al. [3] highlighted the need of real-time damage evaluation in insurance claims by creating YOLOv5-MCD, an enhanced version of YOLOv5 designed for detecting minor and alligator road damages. Deep learning models for car damage identification and cost prediction were studied by Narra and Savitha [4]. In order to assess how well CNN-based architectures like YOLO, Faster R-CNN, and SSD automate insurance claim procedures, their study contrasted them. Li and Zhang [5] demonstrated the versatility of object identification models in damage assessment by putting forth a novel method for road illness detection using YOLOv5s-DSG. Using traffic surveillance footage, Sui et al. [6] investigated accident detection and analysis, showing how AI-driven systems may support insurance automation by offering real-time insights into car damage and accident severity.In their discussion of GPU-accelerated collision analysis in a point cloud setting, Shah et al. [11] showed how useful it is for evaluating vehicle damage. A point cloud registration technique for autonomous driving called Global-PBNet was presented by Zheng et al. [12] and has the potential to improve AI models used in insurance assessments. An automatic registration technique for point clouds and panoramic photos was created by Wang et al. [13], providing advancements in the evaluation of extensive vehicle damage. In order to make damage assessment technologies more accessible, Xiang et al. [14] created Mobile3DScanner, a top-notch object reconstruction tool that uses mobile devices. Lastly, an enhanced LiDAR simulator for autonomous driving was described by Fang et al. [15], which may help improve AI-based damage detection models.The literature analysis emphasizes how object detection and deep learning are becoming increasingly significant in evaluating vehicle damage. Even while AI-driven models like YOLOv5 produce encouraging outcomes, issues with fraud detection, model robustness, and dataset quality still exist. Future studies should concentrate on enhancing the accuracy of real-world detection, using blockchain technology for safe claims processing, and honing hybrid AI models for accurate cost assessment.

III. METHODLOGIES

A systematic approach is used in the "Automated vehicle Damage detection & Cost Estimator for Insurance Companies" project methodology to guarantee precise and effective damage assessment. Data collection is the first step in the process. A variety of vehicle damage photos, including those of two-wheelers and four-wheelers, are collected, labeled with the type and extent of the damage, and then separated into training, validation, and testing sets. For damage detection, YOLOv5, a cutting-edge object detection model, is then used. The model is validated and adjusted to maximize accuracy after being trained on the annotated dataset to identify and categorize different kinds of damage. Once trained, the model is incorporated into the system to detect and categorize faults in real-time car image analysis. Following detection, a cost estimating algorithm determines the cost of repairs based on the damage found, and thorough reports are produced to compile the results. Prior to deployment, the system is put through a thorough real-world testing process and is built with an intuitive interface for insurance firms. Constant updates guarantee flexibility in response to fresh information and human input, gradually increasing accuracy. With its sophisticated architecture that combines CSPNet for feature extraction, PANet for feature fusion, and efficient post-processing algorithms, Ultralytics' YOLOv5 improves real-time object detection. With support for small, medium, large, and extra-large model sizes, YOLOv5 offers a range of speed and accuracy options depending on available computing power.

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1) Data gathering is the first step in the process, where a large dataset of pictures of vehicles, including two-, four-, and six-wheelers, is acquired. To increase the model's resilience, these photos are labeled with damage and gathered in a variety of settings, including different lighting, angles, and vehicle conditions. To make model creation and evaluation easier, the dataset is then separated into subgroups for training (70%), validation (15%), and testing (15%).
2) After that, the input photos are standardized using data preparation. To make sure they are compatible with the YOLOv5 model, all photos are shrunk to a specific dimension, usually 640x640 pixels. In order to facilitate stable model training, normalization is employed to scale pixel values between 0 and 1. Furthermore, to increase dataset variability, decrease overfitting, and improve the model's capacity to generalize to new data, data augmentation techniques including rotation, flipping, and color adjustments are employed.

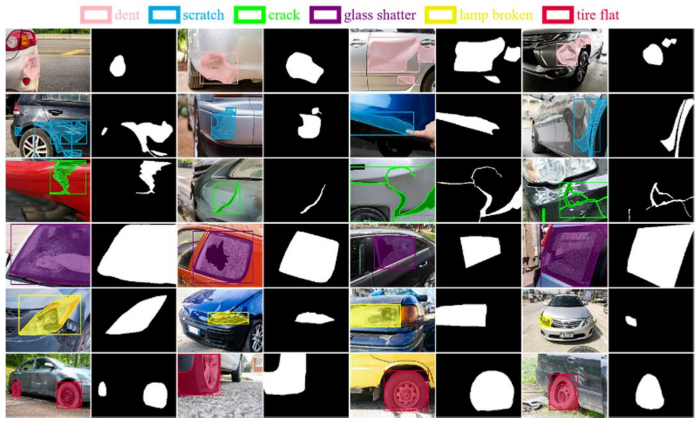

Fig.1 Damage segmentation

During the model training phase, YOLOv5 is trained to identify and categorize vehicle damage. To increase performance and cut down on training time, transfer learning with pre-trained weights is used when it is available. To maximize accuracy and model convergence, hyper parameter tuning involves modifying learning rates, batch sizes, and other factors. Metrics including precision, recall, F1 score, and mean Average Precision (MAP) are used to evaluate the model's performance once it has been trained. To visualize classification performance and spot frequent misclassifications, a confusion matrix is created.

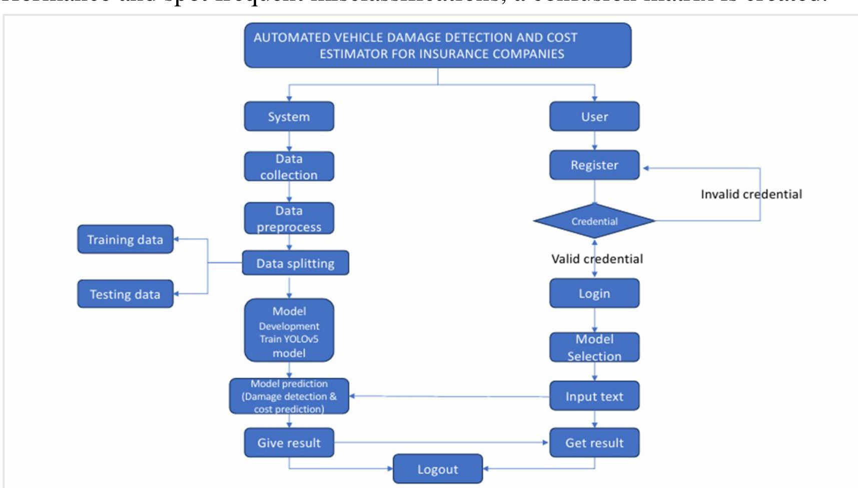

Fig.2 project flow

IV. EVALUATION METRICS

The model's precision and recall over several thresholds are measured by Mean Average Precision (mAP), which yields an overall performance score.Precision, which is computed as

$$AP=n\sum(Rn-Rn-1)Pn$$

$$mAP=N1i=1\sum NAPi$$

$$Precision= TP/(FP+TP)$$

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Where, TP (True Positives) represents correctly identified damage cases.
FP (False Positives) represents incorrectly classified or falsely detected damages.

Shows the proportion of expected damage detections that were actually accurate. The recall of the model, which is computed as indicates its capacity to identify actual damages.

For the purpose of evaluating overall performance, the F1-Score is a harmonic mean of precision and recall. For real-time applications, inference time—a measure of how quickly the model processes an image—is essential. The model's capacity to discriminate between vehicle areas that are damaged and those that are not is examined using the ROC Curve and AUC Score.

$$F1=2\times((Precision+Recall)/Precision\times Recall))$$

V. RESULTS AND ANALYSIS

Images of several vehicle types—two-, four-, and six-wheelers—are collected and labeled with damage under various settings as the first step in implementing the Automated vehicle damage detection and cost estimating system. Then, in order to make model construction easier, the dataset is separated into subgroups for training (70%), validation (15%), and testing (15%).

1).When you upload a picture of the damaged two-wheeler, the system uses artificial intelligence to identify the impacted locations. It categorizes the extent of the damage and calculates the parts and labor costs for repairs. Users can connect with local service centers and receive a comprehensive pricing breakdown. For hassle-free repairs, insurance claims can be integrated.

Fig.3 2wheeler output

Artificial intelligence recognizes dents, scratches, and broken pieces in an automobile photograph that has been uploaded. The system estimates the cost of repairs and classifies the extent of the damage. A breakdown of parts, labor, and paint costs is provided to users. Included are assistance with insurance claims and service center reservations.

Fig.4 4 wheeler output

The system identifies mechanical and structural deterioration in trucks and commercial vehicles. Severity classification and repair cost estimation are provided using AI-based analysis. Users receive information on labor, downtime, and part replacement costs. Insurance claim processing and linkages to fleet service centers are offered.

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Fig.5 6 wheeler output

VI. CONCLUSION

The performance of the YOLOv5 vehicles exhibits both strengths and potential for improvement, with notable variations across various vehicle classifications. With an impressive mean Average Precision (mAP) of 99.07% at an IoU threshold of 0.5, the two-wheeler detection model surpasses all others in terms of precision and recall. Together with a strong mAP_0.5:0.95 and little validation loss, this high accuracy demonstrates the model's superior robustness and generalization. The findings show that the two-wheeler model is incredibly dependable and can consistently detect objects in a variety of settings and conditions.In contrast, the four-wheeler model performs mediocrely, having lower recall and precision than the two-wheeler model. The reduced mAP_0.5:0.95 indicates difficulties in recognizing objects under more stringent overlap criteria, even though the mAP at an IoU threshold of 0.5 is a respectable 77.11%. This suggests that different perspectives, occlusions, and complicated backgrounds may cause problems for the model. The validation losses indicate that while the model functions well, it might be improved, especially in the areas of feature extraction and bounding box prediction refinement. Improving the model's capacity to distinguish between cars in congested or overlapping situations could greatly increase its efficacy.Although the six-wheeler model performs well overall, there is still opportunity for development. It works well most of the time, with a precision of 85.71% and a recall of 89.82%. An promising sign of the model's resilience is its mAP of 91.12% at an IoU threshold of 0.5. A lower mAP_0.5:0.95 indicates difficulties in identifying items with more stringent overlap requirements, though. The model would benefit from more training with a variety of datasets to improve its capaity to identify six-wheelers in a range of illumination and environmental situations, even though the validation losses match training results quite well. Both precision and recall could be enhanced by more fine-tuning, especially when dealing with occlusions and different scales.In summary, the two-wheeler model is the most precise and dependable of the three types, even if they all do well in their respective categories. Despite their effectiveness, the four-wheeler and six-wheeler models need to be improved further to handle their unique detection difficulties. Future research should concentrate on enhancing the models' capacity to manage more stringent overlap circumstances, decreasing false positives, and boosting detection consistency in various settings. Performance could be greatly increased by improving feature extraction procedures, adding sophisticated augmentation techniques, and diversifying datasets. These issues can be fixed to improve the models' generality and accuracy, which will increase their suitability for practical use.

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REFERENCES

[1] S.-L. Lin and Y.-H. Chen, "Technique on vehicle damage assessment after collisions using optical radar technology and iterative closest point algorithm," *IEEE Access*, vol. 12, pp. 174507–174518, Dec. 2024, doi: 10.1109/ACCESS.2024.3495721.

[2] M. Roy and J. Bhaduri, "A computer vision enabled damage detection model with improved YOLOv5 based on transformer prediction head," *arXiv preprint arXiv:2303.04275*, 2023.

[3] G. Liu, S. Li, L. Wang, J. Sun, and S. Chen, "YOLOv5-MCD: Improved YOLOv5 for minor and alligator road damage detection," *Journal of Electronic Imaging*, vol. 33, no. 6, p. 063029, 2024.

[4] S. Narra and N. J. Savitha, "Deep learning-based damage detection and repair cost estimation for automobiles," *International Journal of Innovative Science and Research Technology*, vol. 8, no. 6, 2023.

[5] G. Li and Z. Zhang, "Road disease detection algorithm based on YOLOv5s-DSG," *Journal of Real-Time Image Processing*, 2023.

[6] Y. Sui, S. Zhou, Z. Ju, and H. Zhang, "A vision-based system design and implementation for accident detection and analysis via traffic surveillance video," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 45, no. 2, pp. 171–181, 2022.

[7] Grigorev, A.-S. Mihaita, K. Saleh, and F. Chen, "Automatic accident detection, segmentation, and duration prediction using machine learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 2, pp. 1547–1568, 2024.

[8] T. K. Vijay, D. P. Dogra, H. Choi, G. Nam, and I.-J. Kim, "Detection of road accidents using synthetically generated multi-perspective accident videos," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 2, pp. 1926–1935, 2023.

[9] M. Manzoor *et al.*, "RFCNN: Traffic accident severity prediction based on decision level fusion of machine and deep learning models," *IEEE Access*, vol. 9, pp. 128359–128371, 2021.

[10] D. Mallios, L. Xiaofei, N. McLaughlin, J. M. D. Rincon, C. Galbraith, and R. Garland, "Vehicle damage severity estimation for insurance operations using in-the-wild mobile images," *IEEE Access*, vol. 11, pp. 78644–78655, 2023.

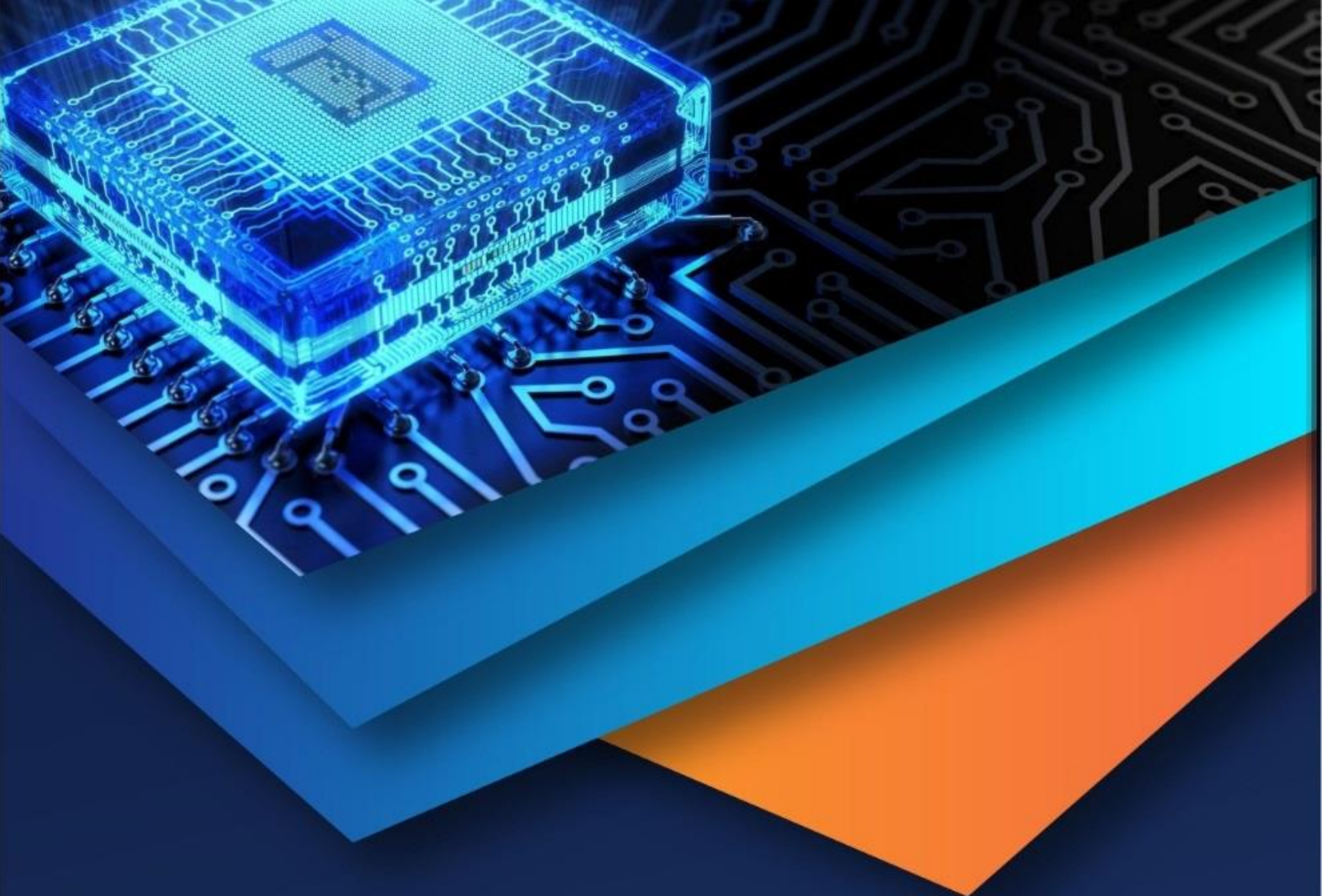
[11] H. Shah *et al.*, "GPU-accelerated collision analysis of vehicles in a point cloud environment," *IEEE Computer Graphics and Applications*, vol. 42, no. 5, pp. 37–50, 2022.

[12] Y. Zheng, Y. Li, S. Yang, and H. Lu, "Global-PBNet: A novel point cloud registration for autonomous driving," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 11, pp. 22312–22319, 2022.

[13] B. Wang *et al.*, "Automatic registration of panoramic image and point cloud based on the shape of the overall ground object," *IEEE Access*, vol. 11, pp. 30146–30158, 2023.

[14] X. Xiang *et al.*, "Mobile3DScanner: An online 3D scanner for high-quality object reconstruction with a mobile device," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 11, pp. 4245–4255, 2021.

[15] J. Fang *et al.*, "Augmented LiDAR simulator for autonomous driving," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1931–1938, 2020.



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