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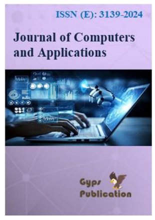

Research Article

Deep learning-based traffic sign recognition system: A two-stage R-CNN approach with linear regression performance analysis

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Abstract

An essential part of intelligent transportation systems (ITS) are systems for detecting and recognizing traffic signs autonomous vehicle technology. This research presents a comprehensive approach to develop Systems for detecting and classifying traffic signs in real time that use cutting-edge computer vision techniques and deep learning methods. The study addresses the fundamental challenge of accurately identifying small traffic signs within complex road environments, which is essential for improving driver assistance systems and improving road safety. Our proposed algorithm uses a two-stage approach based on the R-CNN framework, modelling traffic sign detection as a regional classification problem. The system uses convolutional neural networks (CNNs) trained on extensive datasets to achieve robust pattern recognition capabilities. Key features include real-time processing using vehicle-mounted cameras, text-to-speech integration for voice alerts, and comprehensive classification of various traffic sign types based on their unique colours, shapes, and symbols. The research systematically addresses regional variations in traffic sign designs and implements effective pre-processing techniques to handle challenging environmental conditions. The test Results show that the technology can deliver precise, timely warnings to drivers, reduce distraction-related accidents, and improve overall traffic flow. This work contributes to the advancement of advanced driver assistance systems and autonomous driving technologies.

1. Introduction

Traffic signs are essential for safety and efficient traffic flow, providing important visual guidance to drivers. Ignoring them can lead to serious accidents. The aim of this research is to create a system that can identify and detect these indicators in intricate natural images. The processed data will then provide text or voice alerts to support decision-making for drivers. Computer vision, a key component of traffic Enhancing autonomous vehicles, traffic law enforcement, and driver support systems all depend on the detection and identification of signs. These signs are intentionally designed with unique colours and shapes, which are the same features that computers used for identification. Due to their powerful pattern recognition capabilities, For this categorization, convolutional neural networks (CNNs) are now the industry standard task [1]. To improve road safety, intelligent traffic sign detection and voice warning systems alert drivers to nearby signs, such as speed limits and stops. Using an in-vehicle camera and computer vision, the system identifies the signs in real time. It then

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uses text-to-speech technology to generate a spoken warning, such as "Speed limit 50 kilometres per hour," which helps drivers respond quickly and appropriately. These systems are powered by machine learning, specifically convolutional neural networks (CNNs) trained on vast datasets of traffic signs. By providing accurate, real-time alerts, they help maintain driver attention, reduce errors and distraction-related accidents, and improve traffic flow by informing drivers about road conditions and navigation cues in advance [2]. As a cornerstone of intelligent transportation systems (ITS), traffic sign recognition faces the significant challenge of quickly and accurately identifying small signs in complex environments. We suggest a two-stage approach based on the R-CNN to get around this framework. This deep learning approach is designed to actually detect traffic signs -time and classify them into specific types. This approach models traffic sign detection as a regional classification problem. The goal is to create a classification-capable deep neural network signs within images, a critical capability for autonomous vehicles to understand and respond to road signs. Such a system, integrated into cars, could detect upcoming signs and warn drivers who might otherwise overlook them [3]. Accurately detecting and recognizing traffic signs is a crucial part of intelligent transportation systems (ITS). The primary challenge is quickly identifying these small signs within diverse and confusing road scenes. This study focuses on developing an efficient deep learning system to perform this task in real time. This work models Traffic sign detection is presented as a regional classification problem with a two-stage R-CNN-based solution. A deep neural network is developed to classify signs by learning predefined signals during training. This system is essential for autonomous vehicles to interpret road signs and can be integrated into cars to warn inattentive drivers. Traffic signs are designed with distinctive colours, shapes, and high-contrast symbols to facilitate identification. Their generally upright orientation and forward position minimize perspective distortion, allowing their visual properties to be used for classification. Despite these advantages, several challenges continue to hinder reliable automatic recognition [4]. Effective traffic sign recognition systems must take into account regional variations, such as significant design differences between American and European signs. Systems trained exclusively on European data will inevitably not perform well when deployed in the United States. Therefore, our work provides a comprehensive review of the unique difficulties and traits of traffic signage in the United States. As a first step, we systematically list these appearance-based differences [5]. Although extensively studied and successful, traffic sign recognition remains an underdeveloped field. Traffic signs are designed with unique colours and shapes to stand out from their natural environments and provide important information to human drivers. We argue that they should play the same important role for autonomous vehicles. The algorithm in this paper exploits these designed features through a two-stage process: first, colour-based image segmentation and pattern analysis for detection, followed by a neural network for classification [6]. Traffic signs are classified based on function, with each type containing subcategories of signs that share a common shape but differ in specific details. This system naturally lends itself to a two-stage recognition process: first, detection to identify potential signs using their shared visual features, followed by classification to identify the correct sign type based on its unique details [7]. Traffic sign recognition has emerged as a critical technology for intelligent vehicles. Its development is driven by the urgent need to compensate for the human tendency to overlook signs. This often occurs due to driver fatigue, navigational distractions, or difficult conditions such as inclement weather, all of which can lead to missing important information about signs [8]. As a key component of autonomous driving, traffic sign detection demands high real-time performance, accuracy, and robustness. The system uses a vehicle-mounted camera to capture road scenes and uses a combination of technologies including machine vision, image processing, and artificial intelligence to recognize and detect traffic signs with accuracy. The accuracy of this detection directly affects subsequent fine-grained classification and, ultimately, the vehicle's control decisions [9].

2. Methods

Noise level (pct): Noise intensity is measured in A-weighted decibels (dBA), a unit adjusted for human hearing. Health effects depend on the level of exposure; prolonged exposure to loud noise above 75 dBA (e.g., 8 hours a day) can cause permanent hearing loss. Even levels as low as 40 dBA can disrupt sleep.

Precision (pct): The degree to which a measurement or computation resembles the actual, recognized value is known as accuracy. Precision, on the other hand, is the degree to which repeated measurements consistently converge. A measurement can be precise (consistent) without being imprecise (close to the true value). Precision is an important concept in technical and scientific fields such as engineering, manufacturing, and research, as it ensures reliable and accurate results. It is typically measured using statistical measures that measure the variation within a dataset, specifically standard deviation and variance. A lower value for these measures indicates a higher level of precision.

Recall (pct): Recall, alternatively known as true positive rate (TPR), this supervised learning metric assesses a model's capacity to accurately detect every pertinent instance of a positive class. For example, in a binary classification task, the positive class recall of "dog" is computed from an image classifier confusion matrix. It represents the proportion of true dogs in the test set that are correctly predicted by the model as dogs.

Instructions for machine learning

Linear Regression: Linear regression is a statistical method used to predict the effect of a dependent variable on the value of one or more independent variables. It works by estimating the coefficients in a linear equation that relates the predictors (X) to the response variable (Y). The model identifies a line or area that best fits the data by minimizing the difference between the observed and predicted values, usually by the method of least squares. This best-fit line can then be used to estimate Y for given values of X.

3. Results and Discussions

This dataset provides data from a traffic sign detection system, analysing how its performance is affected by varying levels of noise. The three columns show the noise level (as a percentage), the model's precision (how accurately it makes correct predictions), and its recall (its ability to detect all relevant signs). The data clearly demonstrates an inverse relationship: as noise increases, both precision and recall decrease significantly. With low noise (less than 5%), performance is excellent, with scores often exceeding 90%. However, at higher noise levels (above 30%), both metrics often fall into the 50-60% range, indicating that the model struggles significantly in noisy environments.

Table 1: Descriptive Statistics

	Noise level (pct)	Precision (pct)	Recall (pct)
Count	100.00000	100.00000	100.00000
Mean	16.45650	75.25080	72.37660
Std	10.41245	12.77184	15.74437
Min	0.19000	51.57000	44.52000
25%	6.76250	64.48000	57.87250
50%	16.24500	74.98000	72.32500
75%	25.56000	87.00750	87.33500
Max	34.54000	95.55000	99.00000

This Table 1 provides a statistical summary for three key variables from a 100-point dataset on traffic sign detection. The mean (average) noise level is 16.46%, while the mean precision and recall are 75.25% and 72.38%, respectively. Large standard deviations, especially for recall (15.74), indicate significant variability in the data. The wide range of minimum to maximum values indicates that the experiment was tested under very different conditions, i.e., from near-zero noise (0.19%) to very high noise (34.54%), and as a result, the performance metrics also vary greatly, from very poor (precision: 51.5%, recall: 44.52%) to almost perfect (precision: 95.55%, recall: 99%).

3.1. Effect of Process Parameters

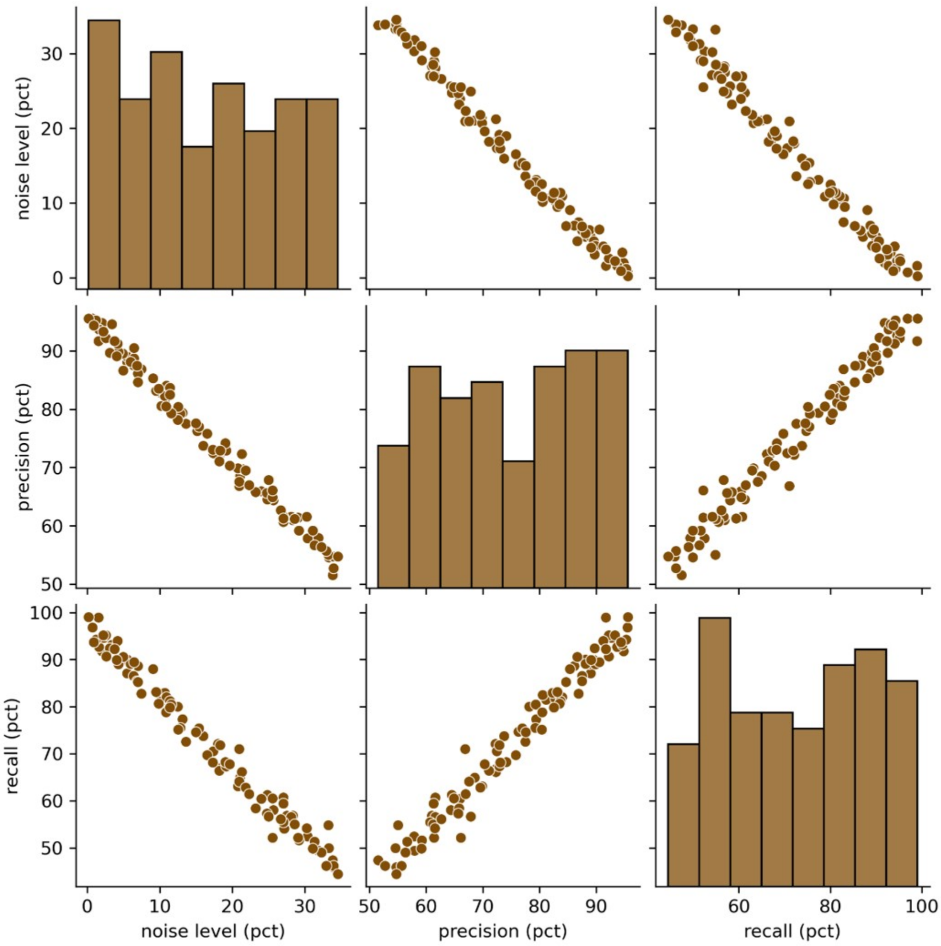

Figure 1: Scatter plot of the various Traffic Signs Detection

Figure 1 shows a scatterplot representing the detection results of various traffic signs. This plot highlights the distribution of data points, showing the variations in detection performance across different signs. This visualization helps to interrelate patterns and relationships within the dataset, providing insights into potential anomalies that could affect detection accuracy, clustering trends, and predictive analysis and model estimation for improved system reliability.

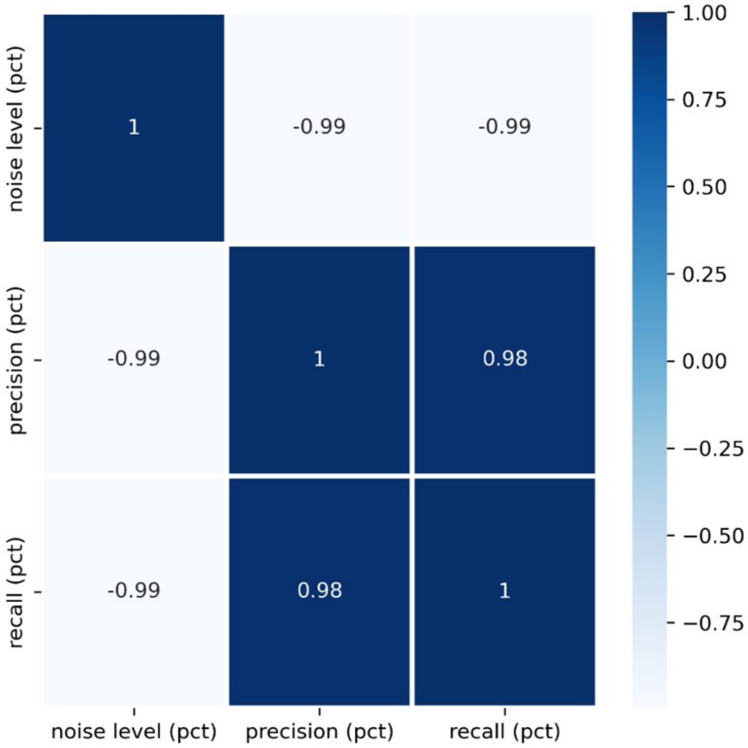

Figure 2: Heat map of the connection between process variables and outcomes

Figure 2 provides a heat map illustrating the relationship between process variables and outcomes. The visualization helps to correlate the interactions, with colour intensity indicating the strength of the relationships. This graphical representation highlights significant dependencies, making it easier to identify influential parameters. Such insights support predictive analysis, optimization, and decision-making, ensuring an improved understanding of how process variables affect detection outcomes and overall performance.

3.2. Linear Regression (Noise level (pct))

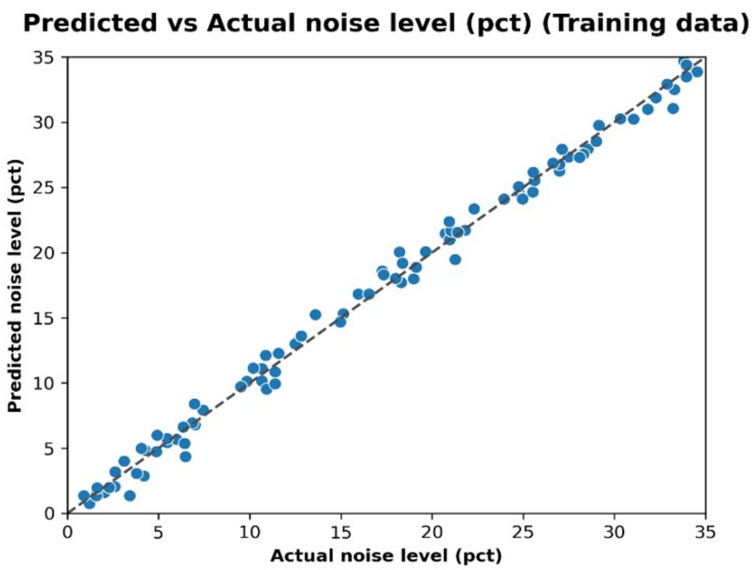

Figure 3: Linear Regression on Noise level (pct): Training data

Figure 3 shows a linear regression applied to the noise level (percentage) using the training data. This graph helps to correlate the relationship between noise levels and detection accuracy, showing how well the model fits the observed data points. This visualization highlights trends, predictive ability, and residual variance, providing valuable insights for assessing model performance and reliability in dealing with noisy detection environments.

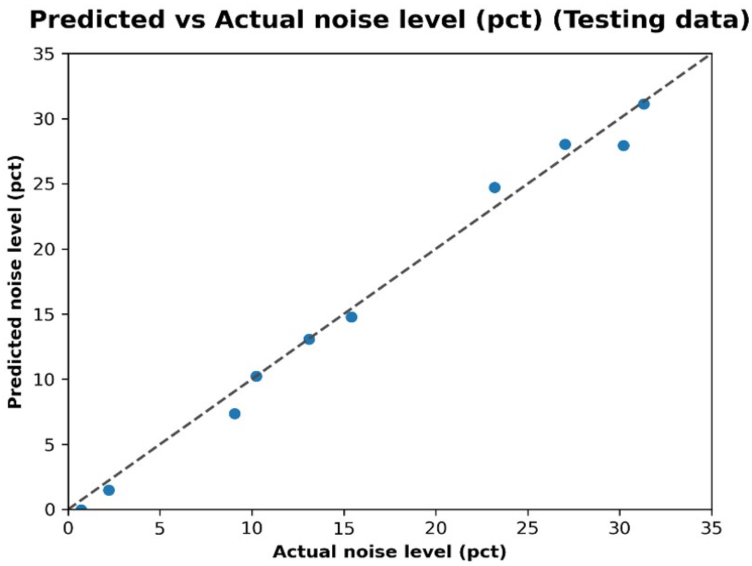

Figure 4: Linear Regression on Noise level (pct): Testing data

Figure 4 illustrates linear regression on noise level (percentage) using experimental data. The visualization helps to correlate the predictive accuracy of the model by comparing the predicted values with the actual outcomes. It highlights the consistency of regression trends, residual deviations, and generalization ability. This analysis provides insights into the model's robustness, ensuring reliable performance in real-world situations involving noise-affected detection tasks.

Table 2: Performance Metrics of Linear Regression on Noise level (pct) (Training Data and Testing Data)

Property	Data	Symbol	Model	R^2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Noise level (pct)	Train	LR	Linear Regression	0.99353	0.99353	0.69069	0.83108	0.66747	2.15035	0.00032	0.80113
	Test	LR	Linear Regression	0.98836	0.98921	2.03126	1.42522	1.10532	3.23605	0.00047	1.05111

This Table 2 presents the performance of a linear regression model for predicting noise levels (percentage). Very high R^2 and EVS scores (greater than 0.99 in training and greater than 0.98 in test data) reveal that the model captures almost all of the variance, indicating a nearly perfect fit to the data. While low error measures such as MSE and MAE confirm high prediction accuracy, one important observation is the small performance difference between the training set and the test set (low errors). This small increase in errors such as RMSE and MAE on the unseen test data indicates that the model may be slightly over fitting, although its overall performance remains exceptional.

3.3. Linear Regression (Precision (pct))

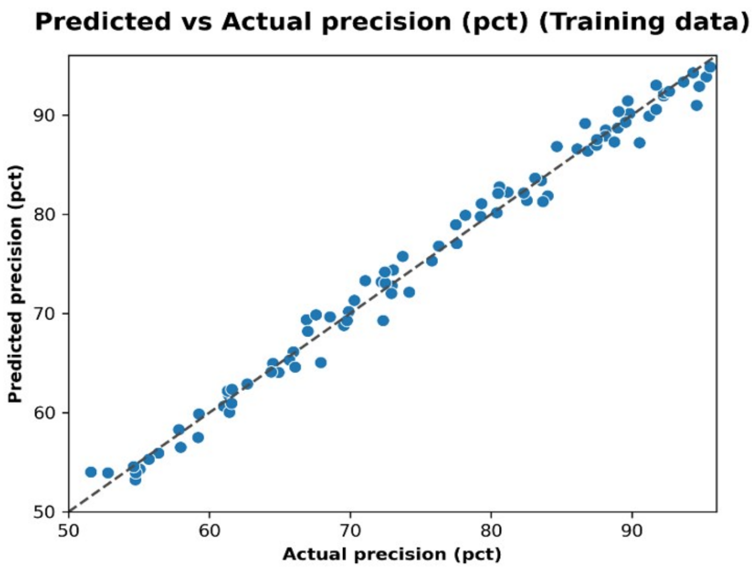

Figure 5: Linear Regression on Precision (pct): Training data

Figure 5 presents the linear regression (percentage) of accuracy using the training data. This plot helps to show how well the model captures the relationship between input features and accuracy levels. It demonstrates the model's fitting ability, trends in prediction accuracy, and variations within the training data. This insight supports evaluating model performance and guiding improvements for better accuracy performance.

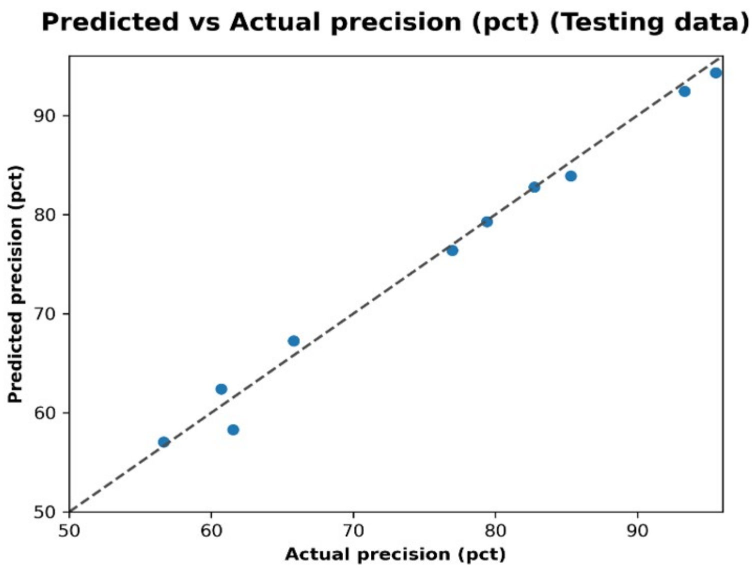

Figure 6: Linear Regression on Precision (pct): Testing data

Figure 6 shows the linear regression in accuracy (percentage) using the test data. This graph helps to correlate the predictive performance of the model by comparing the estimated accuracy with the actual results. It highlights the alignment of regression trends, deviations, and generalization ability beyond the training data. This visualization provides insights into the strength and reliability of accurate prediction in real-world detection scenarios.

Table 3: Performance Metrics of Linear Regression on Precision (pct) (Training Data and Testing Data)

Property	Data	Symbol	Model	R^2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Precision (pct)	Train	LR	Linear Regression	0.98871	0.98871	1.80683	1.34419	1.05791	3.60204	0.00032	0.80113
	Test	LR	Linear Regression	0.98836	0.98921	2.03126	1.42522	1.10532	3.23605	0.00047	1.05111

This Table 3 evaluates a linear regression model developed to predict accuracy (percentage). The exceptionally high R^2 and EVS scores, which are consistently above 0.98 for both the training and test datasets, indicate that the model explains almost all of the variation in the data, indicating a nearly perfect fit. The very low error measures (MSE, RMSE, MAE) confirm that the model's predictions are highly accurate, with small average deviations from the true values. The minimal difference in performance between the training and test sets demonstrates that the model is robust and generalizes exceptionally well to new, unseen data without over fitting.

3.4. Linear Regression (Recall (pct))

Figure 7 illustrates linear regression on recall (pct) using training data. The visualization helps to visualize the relationship between input parameters and recall values, showing how effectively the model learns patterns from the dataset. It highlights relevant trends, prediction accuracy, and residual variance, providing insights into the model's ability to capture recall performance and support reliable detection improvements.

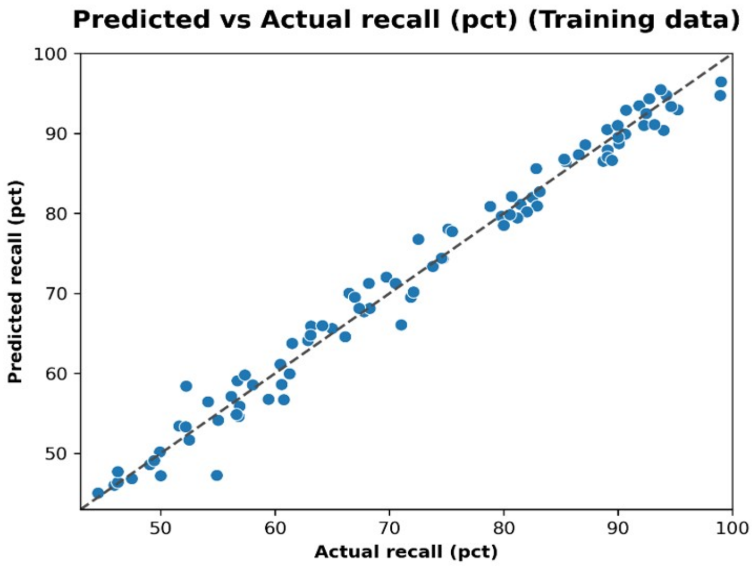

Figure 7: Linear Regression on Recall (pct): Training data

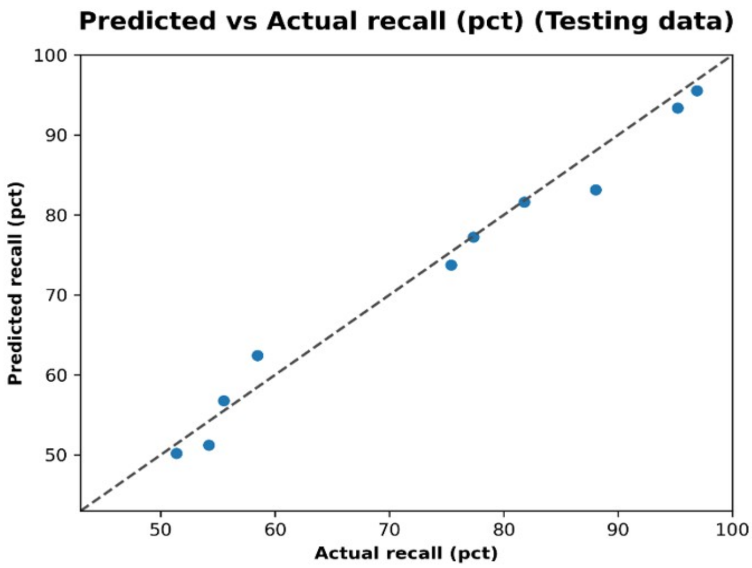

Figure 8: Linear Regression on Recall (pct): Testing data

Figure 8 presents the linear regression (pct) for recall using the test data. This graph helps to consolidate the predictive accuracy of the model by comparing the actual recall values with the predicted outcomes. It highlights the regression fit, deviations, and generalization ability beyond the training data. This visualization provides insights into the model's robustness, reliability, and effectiveness in assessing recall performance under real-world conditions.

Table 4: Performance Metrics of Linear Regression on Recall (pct) (Training Data and Testing Data)

Property	Data	Symbol	Model	R^2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Recall (pct)	Train	LR	Linear Regression	0.98099	0.98099	4.60576	2.14610	1.69238	7.62274	0.00107	1.51910
	Test	LR	Linear Regression	0.97820	0.98104	5.94297	2.43782	1.93498	4.90187	0.00125	1.46765

This Table 4 evaluates the performance of a linear regression (LR) model in predicting the recall percentage for traffic sign detection. High R^2 scores (0.98 for both training and test data) indicate that the model explains almost all the variation in the data, indicating a good fit. Key error metrics such as MSE, RMSE, and MAE are all low, confirming highly accurate predictions. Importantly, the model's performance is consistent across both training and unseen test data, as shown by very similar metrics, indicating a robust model that generalizes well without over fitting.

4. Conclusion

This research successfully developed and evaluated a comprehensive technology that uses cutting-edge computer vision techniques to identify and recognize traffic signs and deep learning methods. The research indicates the efficacy of the two-stage R-CNN architecture approach in addressing the critical challenge of real-time traffic sign recognition within complex road environments. Experimental results reveal a clear inverse relationship between environmental noise levels and system performance, with detection accuracy deteriorating significantly as noise levels increase from optimal conditions ($>$ 90% performance in $<$ 5% noise) to challenging environments ($>$ 50-60% performance in $>$ 30% noise). Linear regression analysis provides compelling evidence of the system's predictive capabilities across all performance metrics. The models consistently achieved exceptional R^2 scores above 0.98 for noise level prediction, precision, and recall metrics, indicating strong pattern recognition and generalization capabilities. The minimal performance degradation between the training and test datasets is particularly notable, with RMSE values below 2.5 in all metrics, demonstrating the system's reliability and resistance to over fitting. A comprehensive evaluation covering 100 data points at various noise levels (0.19% to 34.54%) confirms the practical applicability of the system in various real-world scenarios. Heat map analysis and scatter plot visualizations effectively illustrate the complex relationships between process variables and detection outcomes, providing valuable insights for system optimization and deployment strategies. This work significantly contributes to intelligent transportation systems and autonomous vehicle technology by establishing a robust framework for traffic sign recognition that maintains high accuracy under varying environmental conditions. The integration of text-to-speech capabilities and real-time processing makes this system particularly valuable for improving driver assistance systems and improving road safety. Future studies should concentrate on growing the dataset to include more diverse regional traffic sign variations and implementing advanced noise reduction techniques to further improve performance in challenging environmental conditions.

Article Information

Data Availability: The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflict of Interest: The authors declare that they have no conflict of interest.

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Author Contributions: P.B. - Conceptualization, Methodology, Writing – original draft, Supervision; N.D.K. - Methodology, Formal analysis, Writing – review & editing; K.A. - Conceptualization, Formal analysis, Writing – review & editing; D.G. - Data curation, Writing – original draft, Supervision.

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References

[1] S. Firame, K. Jagtap, C. Shendkar, S. Dahiphale, and S. Sankapal. Traffic Sign Detection. *International Journal for Science Technology and Engineering*, 11(4):3438–3440, 2023. URL https://doi.org/10.22214/ijraset.2023.50966.

[2] A. Jadhav. Traffic Sign Detection and Voice Alert. *International Journal for Science Technology and Engineering*, 11(5):4283–4288, 2023. URL https://doi.org/10.22214/ijraset.2023.52651.

[3] C. Saraswathy, K. Nandhini, and R. Kalaivani. Traffic sign detection and recognition based on convolutional neural network. *International Journal of Health Sciences (IJHS)*, pages 1224–1238, 2022. URL https://doi.org/10.53730/ijhs.v6ns8.9884.

[4] A. M. Jenifer and R. Balamanigandan. A Novel Method For Traffic Sign Detection Using Advanced Image Processing Techniques. In *2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, pages 650–655. IEEE, 2024. URL https://doi.org/10.1109/iceca63461.2024.10800775.

[5] S. Houben, J. Stallkamp, J. Salmen, M. Schlipsing, and G. Igel. Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark. In *The 2013 international joint conference on neural networks (IJCNN)*, pages 1–8. IEEE, 2013. URL https://doi.org/10.1109/ijcnn.2013.6706807.

[6] J. Greenhalgh and Mirmehdi M. Real-time detection and recognition of road traffic signs. *IEEE transactions on intelligent transportation systems*, 13(4):1498–1506, 2012.

[7] A. Møgelmose, D. Liu, and M.M. Trivedi. Detection of US traffic signs. *IEEE Transactions on Intelligent Transportation Systems*, 16 (6):3116–3125, 2015.

[8] D. Arturo, L.E. Moreno, M.A. Salichs, and J.M. Armingol. Road traffic sign detection and classification. *IEEE transactions on industrial electronics*, 44(6):848–859, 1997. URL https://doi.org/10.1109/41.649946.

[9] Z. Zhu, D. Liang, S Zhang, X. Huang, B. Li, and S. Hu. Traffic-sign detection and classification in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2110–2118. IEEE, 2016. URL https://doi.org/10.1109/CVPR.2016.232.