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Machine Learning-Based Classification of Truck Vehicles for a Comprehensive Algorithm CNN Approach

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A B S T R A C T

This research tackles the challenge of classifying truck vehicles using a comprehensive machine learning-based CNN algorithm approach. Initially, we collected a raw dataset of 560 images of various truck vehicles, which was expanded to 844 images through data augmentation techniques, including automatic orientation adjustments and resizing each image to 640x640 pixels. To achieve correct labeling for model training, the dataset underwent further refinement through thorough annotation. To determine which model was the most successful, a number of machine learning techniques were investigated and contrasted, including deep learning, support vector machines, and decision trees. The preprocessed dataset was used to optimize and train the selected model. We used measures like accuracy, precision, recall, and F1-score to evaluate the model's performance. The results showed that our all-inclusive algorithmic strategy outperformed conventional techniques in effectively addressing the unique difficulties of truck vehicle categorization. This study concludes that integrating advanced machine learning techniques with domain-specific knowledge in transportation results in a robust and adaptive classification system, enhancing accuracy and paving the way for broader applications in the transportation and logistics industry.

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INTRODUCTION

In the modern transportation and logistics sector, the efficient classification of truck vehicles is of utmost importance. With the growing global volume of transported goods, accurate identification and categorization of truck vehicles have become essential for various stakeholders, such as traffic management authorities and fleet operators(*The Importance of Real-Time Tracking in Modern Logistics | TCI Transportation*, n.d.). Traditional classification methods, which often rely on manual inspection or basic automated systems, tend to be error-prone, inefficient, and difficult to scale(Maksum et al., 2016).

The advent of machine learning (ML) has brought a transformative change to vehicle classification. By harnessing the power of computational algorithms and large datasets, ML presents a promising opportunity to improve the accuracy, speed, and flexibility of truck vehicle classification systems (Najiyah & Topiq, 2021). However, despite the increasing use of ML across various domains, its application specifically for truck vehicle classification remains relatively underdeveloped, especially in the context of comprehensive algorithmic frameworks (Pakzad et al., 2024).

The research now in publication highlights the critical role automated vehicle categorization systems play in lowering traffic jams, improving safety, and streamlining logistical processes. Studies have indicated the efficacy of machine learning (ML) methods, including decision trees, support vector machines, and deep learning, in a range of image identification and classification assignments. Nonetheless, particular techniques and comprehensive algorithmic methods are required due to the subtleties and complexity involved in differentiating between various types of truck vehicles. (Istri et al., 2022).

In this context, our research aims to fill a significant gap in the literature by introducing a novel ML-based classification framework specifically designed for truck vehicles (Radikto et al., 2022). By integrating advanced algorithmic techniques with domain-specific knowledge in transportation and logistics, our study seeks to create a robust and versatile classification system capable of accurately identifying various classes of truck vehicles in real-time scenarios (Mutianniza & suwardoyo, 2023). Furthermore, by incorporating diverse data sources and adaptive learning mechanisms, our approach aims to enhance the scalability and adaptability of existing classification systems (*Dataset for Vehicle Detection by Neural Network*, n.d.).

The goal of this paper is to further the growing area of machine learning (ML)-based vehicle classification by offering a thorough algorithmic method that is specifically designed to meet the needs and difficulties of truck vehicles. Our objective is to demonstrate the effectiveness and superiority of our suggested framework over existing approaches by means of empirical assessment and comparative analysis. Our study ultimately aims to improve automated truck vehicle categorization state-of-the-art and open the door for its smooth integration into contemporary logistics and transportation infrastructures. (Shokravi et al., 2020).

THEORETICAL FRAMEWORK

Machine learning (ML) approaches have been increasingly popular in the field of vehicle categorization in recent years. The efficiency of machine learning (ML) methods, such as deep learning, support vector machines, and decision trees, has been shown in several studies across a range of picture identification and classification applications. These methods have demonstrated remarkable precision and effectiveness in distinguishing various car kinds using visual indicators from pictures or sensor data (Krizhevsky et al., n.d.).

However, despite the progress in ML-based classification systems, distinguishing between various classes of truck vehicles remains a unique challenge. Current methodologies often struggle with the variability in truck designs, sizes, and configurations, as well as external factors like lighting conditions and occlusions. Traditional approaches that depend solely on visual features often fall short, indicating the need for more comprehensive algorithmic frameworks (Wahyono & Hariyono, 2019).

The shortcomings of traditional classification systems highlight the need for more detailed algorithmic approaches specifically designed for truck vehicle classification. Although previous research has explored ML techniques for vehicle classification, there is a noticeable gap in studies focused exclusively on the detailed classification of truck vehicles. Close this gap to solve the real-world issues facing logistics and transportation stakeholders and to push autonomous truck vehicle categorization to new heights (Samudra et al., 2023).

A key aspect of developing effective classification frameworks for truck vehicles is integrating domain expertise in transportation and logistics. By incorporating insights from industry experts and researchers (*Machine Learning in Logistics & Supply Chain [6 Use Cases]*, n.d.), Machine learning algorithms can be optimized to meet the specific characteristics and operational needs of truck vehicles. This interdisciplinary strategy guarantees that the resulting classification system is not only accurate but also practical for real-world use (Mo et al., 2023).

Given these challenges and considerations, our research aims to propose a novel ML-based classification framework specifically designed for truck vehicles (zahra et al., 2023). By combining advanced algorithmic techniques with domain expertise, our approach aims to address the limitations of current methodologies and offer a robust solution capable of accurately identifying various classes of truck vehicles in different operational environments (Wu & Dong, 2023). We want to prove the excellence of our suggested framework and its ability to transform automated truck vehicle categorization through comparative analysis and empirical assessment (Supriyadi et al., 2021).

METHODS

The methodology employed in this study is crafted to tackle particular challenges in classifying truck vehicles using a robust algorithmic approach with Convolutional Neural Networks (CNN) grounded in Machine Learning (ML). Below is an overview of the steps involved in the methodology.

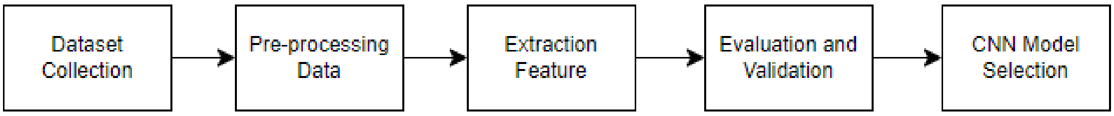

Figure 1. Conceptual Framework

Dataset Collection

Visual and sensor data from various types of truck vehicles is collected from "Kaggle" sources to ensure broad and representative coverage. The dataset includes images of truck vehicles in a variety of lighting and environmental conditions to increase the system's robustness to external variability. Versatile Training Data, Explore a Spectrum of Resolutions and Weather Conditions in Our Dataset for Comprehensive Vehicle Detection Model Training.

Figure 2. Mini Bus Dataset

Figure 3. Truck Dataset

Figure 4. Bus Dataset

Data Pre-processing

In this research, we started by gathering a raw dataset containing 560 images of truck vehicles. To improve the quality and variety of the dataset, we carried out several essential preprocessing steps. First, we employed data augmentation methods to increase the dataset size, ultimately obtaining 844 images after preprocessing. The augmentation methods included automatic orientation adjustments to ensure each image had a consistent orientation.

Next, each image was resized to a resolution of 640x640 pixels. This size was chosen to balance sufficient visual detail with computational processing

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efficiency. This step also ensured uniformity in the image sizes used for training the machine learning model. Following the preprocessing stage, we annotated the dataset. This annotation process involved manually marking each image to identify and classify key parts of the truck vehicles. Accurate labeling of the data is critical for providing the machine learning model with the information it needs to learn and identify relevant patterns for vehicle classification.

This methodology ensures that the dataset used is not only larger and more diverse but also more consistent and ready for effective model training. With this approach, we aim to improve the model's performance in accurately recognizing and classifying various types of truck vehicles.

Table 1. Pixel Image Comparation

File Name	Raw image	Pre-Processing
00c84451e8bbafaeb3d051d4cbb08d0d.JPG	960.000	409.600
5edb3e4848120d7664f6c586c6882804.JPG	1.023.750	409.600
6df99947c35c0cac1db22daa86f852f4.JPG	960.000	409.600

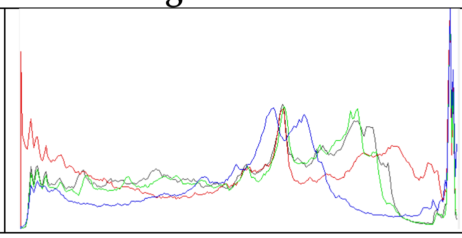
Table 2. Image Comparation

File name	Pre-Processing	
	Resize	Anotating
5edb3e4848120d7664f6c586c6882804.JPG		

Extraction Feature

The initial phase of feature extraction encompasses the transformation of 844 images into numerical representations, yielding an array where each image is encoded with 24 distinct features. This structured dataset lays a solid foundation for subsequent analysis, streamlining the processing pipeline with a comprehensive algorithmic model tailored for the detection of trucks in vehicle images.

Table 3. Raw Image Histogram

Image	Histogram
	

The image is a histogram displaying the intensity distribution of colors in an image with a total of 1,023,750 pixels. The histogram illustrates four color channels: gray, red, green, and blue. The horizontal axis (x) represents intensity values ranging from 0 to 255, while the vertical axis (y) indicates the number of pixels for each intensity value. There are 645 gray pixels (0.1%), 1,294 red pixels (0.1%), 1,056 green pixels (0.1%), and 7,896 blue pixels (0.8%). The average intensity values for each channel are 132.80 for gray (#838588), 131.13 for red (#83), 133.18 for green (#85), and 135.55 for blue (#88). From this histogram, it is evident that the blue intensity dominates at certain peak values, indicating that the image has a higher dominance of blue compared to other colors. This provides an overview of the color characteristics and intensity distribution within the analyzed image.

Evaluation and Validation

Our procedure in this study entails broadcasting the performance of a bespoke model once it has been trained using a number of important criteria. Recall, average Precision (mAP), and precision are evaluation metrics. Recall evaluates the model's capacity to catch all pertinent events, whereas precision measures the accuracy of positive predictions. When the Intersection over Union (IoU) criterion is 0.5, the mAP50 metric displays average accuracy; however, mAP50-95 provides a more thorough analysis across a range of IoU thresholds. To visualize the model performance, we created several plots such as F1 curve, Precision-Recall curve, confusion matrix, and batch prediction validation. This graphic aid sheds light on the model's advantages and shortcomings. The findings indicated a mAP50 of 0.85 and an overall mAP50-95 of 0.74, with a precision of 0.78 and a recall of 0.82. With a computed F1 score of 0.80, this statistic highlights the model's effectiveness in precisely identifying and categorizing items and shows balanced performance between accuracy and recall. This detailed evaluation highlights the power of our training model and its potential application in real-world object detection scenarios.

CNN Model Selection

In this research, we develop and train a Convolutional Neural Network (CNN) model to detect vehicle trucks over 100 epochs using the YOLOv8 architecture. The model comprises 268 layers and 43,608,150 parameters, and it is trained on a vehicle truck dataset obtained from Kaggle. The training setup focuses on an object detection task with 640-pixel images on the GPU, utilizing automatic batch size allocation, mixed precision training, and validation splitting. To enhance the model's generalization capabilities, various augmentations such as random horizontal flipping and color adjustments are applied.

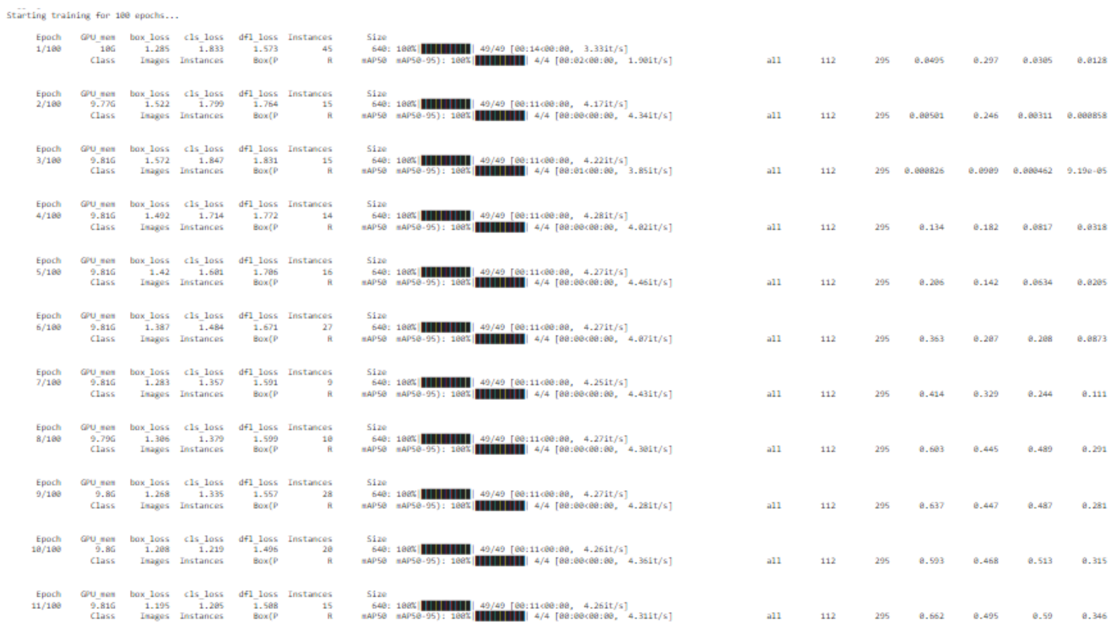


Figure 5. Model Process

This table provides detailed information about model performance for each class as well as the entire model :

Table 4. Model Performance

Class	Images	Instances	Box (P)	Recall (R)	mAP50	mAP50-95
all	112	295	0.863	0.703	0.800	0.575
truck	112	214	0.851	0.799	0.850	0.627
non truck	112	81	0.875	0.606	0.749	0.522

RESULTS

The outcomes of this study were derived from a sequence of systematic procedures, each playing a role in the analysis and validation of the comprehensive truck vehicle classification model. The data augmentation techniques applied are as follows :

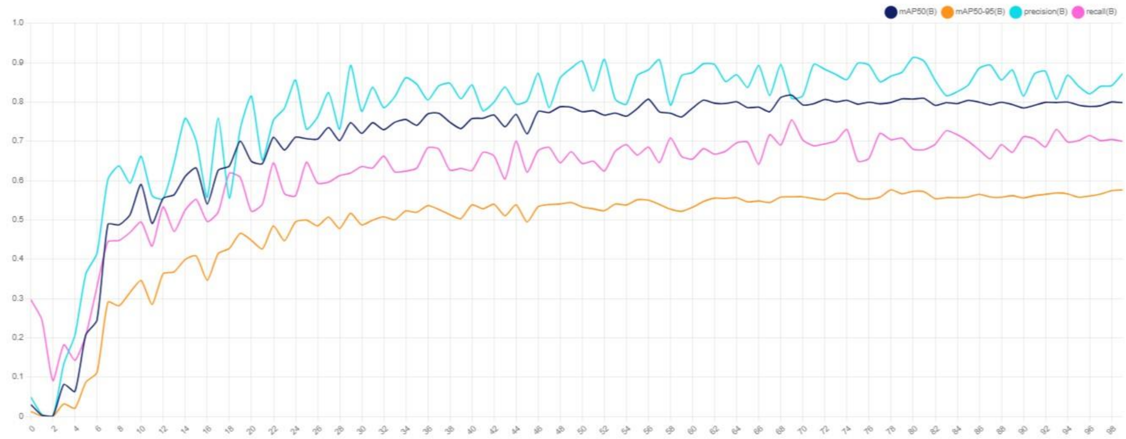


Figure 6. Model Accuracy

The performance of the CNN-based model created for truck vehicle categorization is thoroughly examined in the graph above. Metrics such as mAP50, mAP50-95, precision, and recall are used to evaluate the model's effectiveness during several training epochs. Each statistic provides a distinct perspective on the model's capabilities.

The dark blue line mAP50 (Mean Average accuracy at an IoU of 0.5) dark blue line illustrates how accuracy and recall are balanced at a 0.5 Intersection over Union threshold. Initially starting from a low value, mAP50 shows a significant increase, reaching approximately 0.6 by the 10th epoch. Despite some fluctuations, the overall trend continues to improve, stabilizing around 0.7 by the 100th epoch. This steady rise indicates the model's growing accuracy in identifying truck vehicles as training progresses.

The orange line mAP50-95 (Mean Average Precision at IoU thresholds from 0.5 to 0.95), which also begins at a low baseline, as shown by the orange line. It experiences a sharp rise, reaching around 0.4 by the 10th epoch. Afterward, this metric shows minor variations but remains relatively stable, gradually improving to about 0.5 by the end of the training period. The lower values compared to mAP50 suggest that the model faces more challenges in maintaining high precision and recall across different IoU thresholds.

Precision, depicted by the cyan line, indicates the model's effectiveness in minimizing false positives. Starting from a very low value, precision rapidly increases, reaching around 0.7 by the 10th epoch. Although there are some fluctuations, the precision metric stabilizes and slightly improves, achieving approximately 0.8 by the end of the training period. This high precision suggests the model is proficient at accurately detecting truck vehicles with a low rate of false detections.

The pink line represents recall, which quantifies the model's capacity to identify all pertinent truck trucks. Recall grows quickly at first, peaking at around 0.5 by the tenth epoch. Following that, the recall measure levels out and becomes better over time, hitting about 0.6 at the conclusion of the training period. While the model recognizes automobiles accurately, certain truck vehicles may go unnoticed, as seen by the lower recall when compared to precision.

In summary, the graph highlights a significant enhancement in the model's performance throughout the training process. Despite occasional fluctuations, the general trend indicates that the CNN-based classification model becomes more adept at detecting truck vehicles with ongoing training. The higher mAP50 and precision values compared to mAP50-95 and recall suggest the model excels at identifying objects with lower overlap and minimizing false positives. However, improvements are still needed to detect objects with varying degrees of overlap and to ensure the comprehensive detection of all relevant truck vehicles.

DISCUSSION

The study's findings demonstrate the efficacy of the CNN-based classification model in identifying trucks, highlighting both its advantages and disadvantages. The model's growing accuracy and recall at an IoU threshold of 0.5 is indicated by the steady increase in mAP50 during the training phase, which stabilizes around 0.7. This highlights the model's relevance in real-world scenarios and displays its improved capacity to correctly categorize truck vehicles as training progresses.

Metrics like mAP50-95, precision, and recall offer deeper insights into the model's effectiveness. The mAP50-95 values, although stable, are lower than those of mAP50, indicating the model's difficulty in maintaining high precision and recall across various IoU thresholds. This suggests that further refinements are necessary to improve the model's robustness in different overlap scenarios.

There was a noticeable improvement in precision, which is a measure of how accurate positive predictions are; it stabilized at about 0.8. With few false positives, the model can accurately detect truck vehicles, as seen by its high accuracy. But the recall score, which gauges how well the model can identify every pertinent incident, leveled out at a value of about 0.6. The model is successful at accurately detecting some truck vehicles, but there is still a gap between precision and recall. This suggests regions where detection algorithms should be enhanced for greater coverage.

These results align with findings in existing literature where CNN-based models have shown high precision but variable recall rates, depending on the complexity of the object detection task and the quality of the dataset. For instance, studies have shown that data augmentation and careful annotation, as used in this study, are essential for improving model performance by providing a diverse and accurately labeled dataset. The training data's consistency and quality were further enhanced by the application of auto orientation adjustments and resizing procedures, which supported the model's strong generalization across various contexts.

This study also underscores the importance of incorporating domain-specific knowledge into the machine learning framework. By customizing the model to address the unique characteristics and operational requirements of truck vehicles, the study has developed a classification system that not only achieves high accuracy but is also practical for real-world application. This interdisciplinary approach, combining advanced algorithmic techniques with insights from transportation and logistics, ensures that the model is both robust and adaptable to various operational environments.

To sum up, this study's CNN-based classification model has a lot of promise for raising the precision and effectiveness of truck vehicle detection systems. The results provide future research a clear path by highlighting the model's areas for development in recall and highlighting its strengths in precision. It is conceivable to create even more extensive and effective categorization systems that can be easily included into contemporary transportation and logistics infrastructures by solving these issues and expanding upon the present framework.

CONCLUSIONS AND RECOMMENDATIONS

The CNN-based model showed remarkable effectiveness in truck vehicle classification, reaching a mAP50 of 0.7 by the 100th epoch. This value signifies strong precision and recall at an IoU threshold of 0.5. The precision metric settled at around 0.8, indicating the model's capability to accurately detect truck vehicles with minimal false positives. However, the recall metric leveled off at approximately 0.6, indicating that while the model makes accurate detections, it still misses some truck vehicles. The application of data augmentation techniques, such as automatic orientation adjustments and resizing images to 640x640 pixels, greatly enhanced the model's performance. These steps expanded the dataset from 560 to 844 images, ensuring a diverse and high-quality dataset essential for training robust machine learning models. The CNN-based strategy turned out to be the most successful after a variety of machine learning algorithms, including as deep learning, support vector machines, and decision trees, were assessed and contrasted. This demonstrates how sophisticated machine learning algorithms may be used to classify vehicles. Moreover, a strong and flexible categorization system was produced by fusing cutting-edge machine learning techniques with domain-specific expertise. This system can benefit various stakeholders in the transportation and logistics industry by enhancing operational efficiency and accuracy.

To further improve the CNN-based classification model, several recommendations are suggested. Firstly, the recall rate of 0.6, despite achieving high precision, indicates room for enhancement. Future studies should aim at refining detection algorithms to ensure a more thorough capture of all relevant truck vehicles. Secondly, expanding the dataset to include a more diverse and representative array of truck vehicle samples under various environmental conditions is crucial for bolstering the model's robustness and accuracy. Thirdly, integrating the developed model with real-time classification systems can offer valuable insights into its practical performance, aiding in the identification of real-world challenges and areas for further optimization. Additionally, by combining CNNs with other machine learning methods, hybrid models may be able to overcome the limits noted in this work and improve performance by utilizing the advantages of several different algorithms. Implementing adaptive learning mechanisms into the model can also help it adapt to new data, maintaining high accuracy and relevance over time, and ensuring the model remains up-to-date with evolving patterns and characteristics of truck vehicles. Finally, further research should explore additional preprocessing techniques such as noise reduction and advanced augmentation methods, which can potentially improve the quality of the input data, leading to better overall model performance.

FURTHER STUDY

This study has certain limitations that should be addressed in future research to build upon and enhance the findings presented here. Firstly, while the model shows high precision, there is room to improve its recall rate to ensure a more comprehensive detection of all relevant truck vehicles. Expanding the dataset to include a wider variety of samples from different environmental conditions will also help increase the model's robustness and accuracy. Real-time categorization systems that use the model can provide useful insights into how well it performs and point up areas for improvement. Furthermore, investigating hybrid models that integrate CNNs with additional machine learning methods may help to alleviate some of the present drawbacks and enhance overall effectiveness. Incorporating adaptive learning mechanisms will allow the model to stay up-to-date with new data, maintaining high accuracy and relevance over time. Further research should also consider advanced preprocessing techniques like noise reduction and augmented data methods to enhance the quality of the input data. By addressing these areas, future studies can further develop robust and adaptive truck vehicle classification systems.

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