Deep Learning-Based Generalized Efficient Layer Aggregation Network for the Detection of Coal Trucks

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***Abstract* – Coal transportation is a critical aspect of mining operations, involving the transfer of coal from extraction sites to loading areas. Previous studies have emphasized the effectiveness of object detection models, such as YOLO (You Only Look Once), in monitoring and identifying vehicles to improve safety and efficiency on transportation routes. However, accurately detecting coal trucks remains challenging due to their unique structural and operational characteristics. This study aims to evaluate the effectiveness of the YOLOv9 algorithm in detecting coal trucks compared to earlier YOLO models. The hypothesis suggests that YOLOv9 will outperform previous YOLO versions in terms of accuracy, recall, and overall performance metrics. Using an experimental design, a secondary dataset of 42 images was utilized, divided into 70% for training, 19% for validation, and 11% for testing. Multiple YOLO models were trained and assessed using standard evaluation metrics, including the confusion matrix.**

The results demonstrated that YOLOv9 achieved superior performance, with an F1 score of 79% and a 100% recall rate, surpassing its predecessors. These findings indicate that YOLOv9 is a promising tool for accurate coal truck detection, offering potential improvements for safer and more efficient monitoring systems in coal transportation logistics.

***Keywords* - Coal truck, deep learning, detection, coal transportation logistics**

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1. Introduction

In addition to being regarded as a potential source of revenue for the local community, the abundance of natural resources in a region is also considered to be a requirement for effective and sustainable management that takes into consideration environmental concerns. To achieve sustainable productivity and environmental balance, including the extraction of coal resources, it is essential for all stakeholders involved in its exploitation to work together and coordinate their efforts. This includes governmental, private, and public entities. The coal sector is the most important contributor to national output since it is widely recognized as an essential source of energy for the advancement of society [1]. This urgent work in present energy development is to construct a diversified energy supply system and hasten the energy transition [2]. This task is aligned with the goals of summit meetings and carbon neutrality, and it is extremely important. Utilizing coal resources in a manner that is both socially and environmentally responsible is the goal of addressing the negative environmental repercussions that are linked with the transportation of coal over national roads [1].

The development of intelligent coal mining equipment with the goal of utilizing coal resources in a manner that is both environmentally friendly and efficient has been a primary focus in the modern coal business [3].

This includes mining and production as well as the extraction of coal. The transit of coal from the mining site to the loading site refers to the process of coal transportation, which is an essential component of coal mining operations. In order to improve the overall productivity and efficiency of coal transportation activities, transportation plays a key role [4].

A substantial amount of mineral resource potential may be found in the province of Jambi, which is one of the areas. The procedure of moving coal from a mining site in the western province of Jambi to a port in the eastern province of the country is now a challenge. Coal resources are a significant contributor to the economy. Coal-carrier trucks that are overloaded have caused damage along the highways that they go through, which has caused problems for the province of Jambi. The average total weight of coal-carrying cars was 16 tons in 2021, which was more than the supporting capacity of the roads at the time, 8 tons. This was according to observations made in the field. Overloaded trucks have caused a variety of negative effects since 2009, including damage to roads, financial losses for road repairs that are borne by the local government, frequent traffic accidents, and structural damage to housing foundations near roads as a result of overloaded coal trucks during peak hours, which contributes to congestion on several roads within Jambi City [5].

Due to the fact that the mines that contain stockpiles are located in different areas and there are no highways that are specifically designated for the transportation of coal, the majority of the transportation of coal in the province of Jambi is accomplished through long-distance transportation operations. In order to reduce the negative effects on society, there is an urgent requirement to monitor the movement of coal [6]. On the other hand, failures in surveillance frequently result in coal trucks breaking traffic restrictions, which in turn leads to accidents that are caused by insufficient field monitoring. Therefore, it is necessary to have a considerable amount of human resources available in order to monitor each coal transportation route hence to reduce the number of accidents and traffic infractions [7]. In a worst-case scenario, the accumulation of coal trucks near mines and along national roads due to the difficulty of reaching stockpiles could cause production losses, prompting the Jambi government to intervene to address coal transportation issues [8].

For this reason, the identification and monitoring of coal trucks in a timely manner are of the utmost importance when it comes to the supervision of coal traffic along national routes in the province of Jambi.

As state monitoring technology advances, vehicle monitoring methods have gradually evolved from manual inspection to traditional image recognition algorithms and deep learning-based object detection methods. The manual inspection method is inefficient and expensive. Unlike traditional image identification algorithms, deep learning-based detection techniques do not require manual feature extractor designs and have stronger feature extraction capabilities, thus meeting the demands of efficient and accurate data processing in the age of big data [9]. The YOLO-based truck detection system has been proposed in several papers. However, specifically for the detection of coal truck carriages, no one has yet discussed it. The system proposed in this study uses YOLOv9 as a basic model and combines various improvements to enhance its detection capabilities. These improvements include the use of attention mechanisms such as the Swin Transformer [10], research conducted by C. Liang proposes the YOLOv5s-THSE model, integrating a multi-head attention mechanism, Cross Stage Partial Squeeze-and-Excitation module, and a small object detection head to enhance the accuracy of detecting infrared tank targets in complex ground backgrounds compared to previous methods [11]. The deep learning architecture based on YOLOv4 is proposed to detect freight vehicles. The YOLOv4 algorithm was enhanced by modifying the DarkNet backbone tissue and adding a thin layer of features to detect focused small objects [12]. The enhanced algorithm achieved a 4.76 percentage point increase in mAP metrics on the BDD100K dataset, with a significant improvement in detection accuracy for cars, trucks, and bus categories [13]. Additionally, techniques such as FPN+PAN [14] have shown improved performance in terms of average precision (mAP) and detection time, making it suitable for real-time coal delivery detection applications.

Previous versions of the YOLO object detection algorithm (OD) have been compared and evaluated in terms of their performance in object detection. The results showed that YOLOv7 outperforms other versions in terms of speed and accuracy [15]. YOLOv7 is the fastest algorithm, completing ODs in less than 17.4 milliseconds, and has the highest detection rate for most classes in the datasets [15]. Earlier research compared the YOLOv2 and YOLOv3 algorithms and found that YOLOv3 has superior performance in speed, detecting objects in an average of 2.5 seconds, compared to YOLOv2, which took 43 seconds [16]. YOLOv2 yielded better results in 5 out of 9 classes, while YOLOv3 performed better in recognizing small objects [17].

Although vehicle object detection techniques continue to progress, contemporary algorithms still rely on large amounts of computing resources, in addition to VGA card acceleration, to achieve optimal processing accuracy and speed.

These algorithms typically emphasize the integration of multi-scale features that focus on easily distinguishable global features but tend to ignore complex details, thereby affecting the detection of coal-carrying vehicles in dense views or smaller targets. To overcome such constraints and achieve a balance between accuracy and speed detection, especially in complex environments such as adjacent vehicles, this study introduces an algorithm for detecting coal transportation based on Computer Vision through the YOLOv9 approach. YOLOv9 is the latest iteration of the Chien-Yao Wang and his colleagues' YOLO series [18], released on February 21, 2024.

It is an advancement of YOLOv7, both developed by Chien-Yao Wang and his colleagues.

YOLOv7 makes a significant step in optimizing the training process with what is called a free trained bag, which effectively increases the training efficiency to improve the accuracy of object detection without adding inference costs. However, YOLOv7 does not specifically address the problem of information loss during the process of feed-forwarding input data, a challenge known as the information barrier. This problem arises from scaling down operations in the network, which can weaken critical input data. Existing solutions such as reversible architectures, masked modeling, and deep supervision help reduce information congestion, but the above methods have different weaknesses in the training and inference process. They are also less effective for smaller model architectures, which are important for real-time object detection like those in the YOLO series.

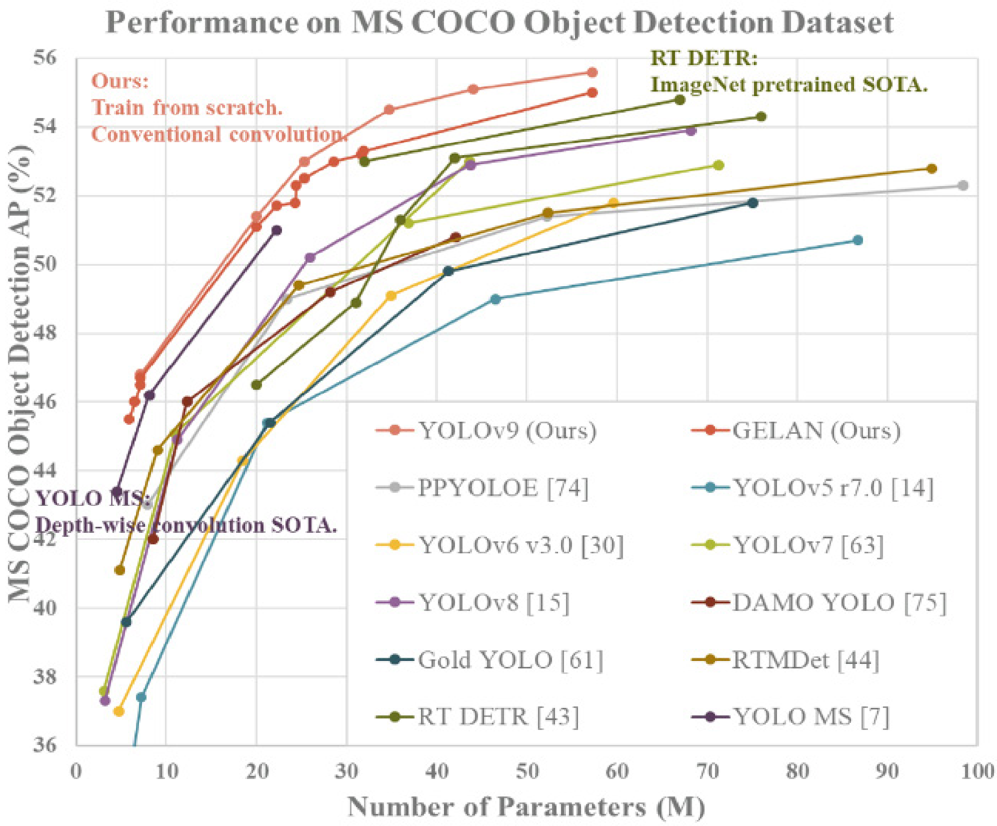


Figure 1. Comparison of real-time object detectors on the MSCOCO dataset

Figure 1 shows that to mitigate this challenge, YOLOv9 incorporates two pioneering methodologies, Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN), to directly address the information bottleneck issue, thus augmenting the precision and efficiency of object detection processes.

The objective of this study is to refine the detection capabilities concerning the identification of coal transportation vehicles, irrespective of their movement status or stationary presence on national highways, with the aim of bolstering coal transportation surveillance.

This will be achieved through the deployment of a detection system capable of accurately classifying vehicles by type. The aspiration is that this system will be comprehensively implemented and operationalized within the framework of national roadway coal transport monitoring.

2. Methodology

This research aims to develop an object detection model based on the YOLOv9 algorithm to improve accuracy in detecting coal trucks on national transportation routes. The research methodology can be explained as follows.

2.1. Research Procedure

The research procedure involved several phases. Initially, data collection, labeling, and selection of the most appropriate version of YOLOv9 to detect coal-carrying vehicles were conducted. Subsequently, matching the coal-carrying vehicles with the developed model was performed. The final phase focused on refining the detection of coal-carrying trucks, as depicted in Figure 2.

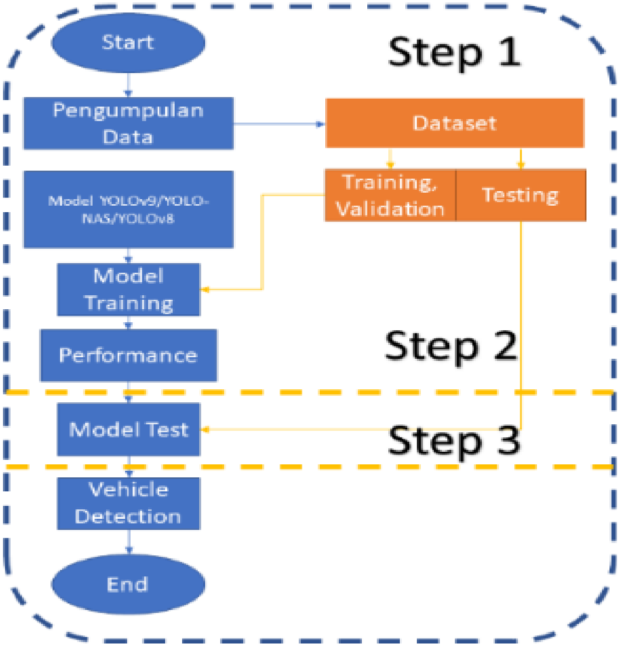


Figure 2. Research procedure

2.1.1. Dataset

High-quality data is crucial for effectively training CNN models; however, data regarding coal transport trucks remains scarce, considering that not all transport trucks are meant for coal transportation. Although a large public dataset is available, data on coal-carrying vehicles passing through national roads are significantly different due to specific size standards. In Jambi Province, coal transport trucks have distinct characteristics, particularly evident in the form of the vehicle tarpaulin, as depicted in Figure 3a and 3b. These trucks have detailed specifications and a unique appearance when carrying coal.

Data on coal-carrying vehicles were collected through documentation from the Jambi Provincial Transportation Agency and Google searches, resulting in a dataset comprising 47 images of coal transport truck vehicles.

(a)

(b)

Figure 3. Coal-carrying truck (a) (b) expedition truck

2.1.2. Labeling (Annotation)

The labeling phase in this study utilizes the Roboflow platform. The versatile, cloud-based Roboflow platform offers a set of features that play an important role in the project's annotation phase.

It enables images to be annotated by a group of people using multiple devices, rather than just one device, allowing the workload to be divided among several individuals (Figure 4).

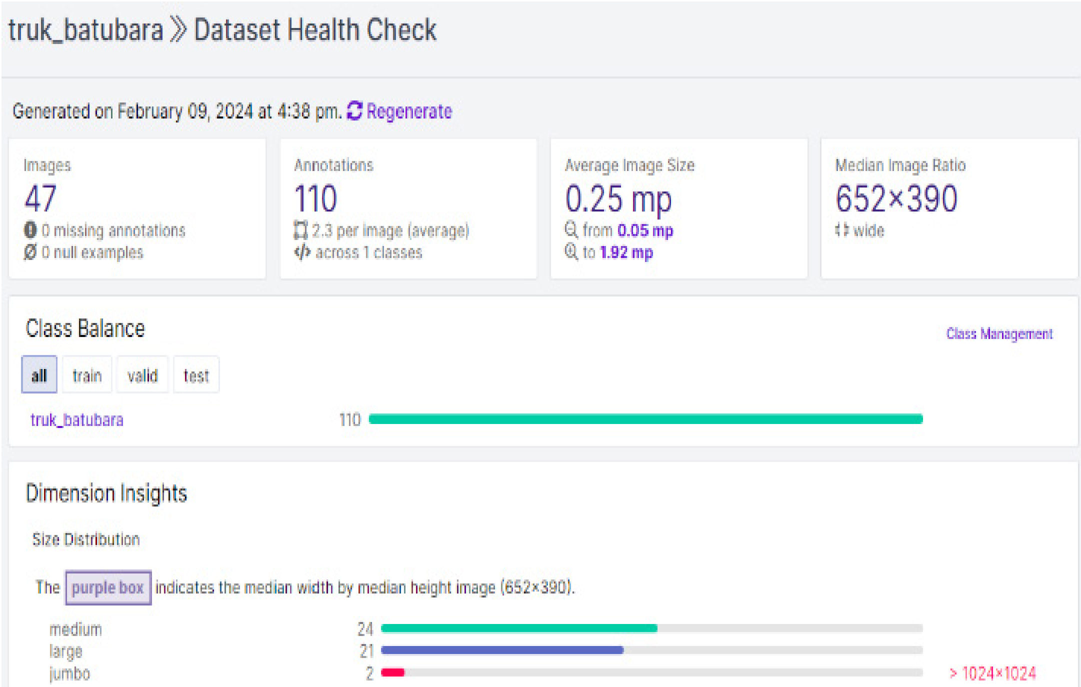


Figure 4. Health dataset checking

Data that is uploaded later can be labeled directly onto images using Roboflow annotate, as illustrated in Figure 5. When starting from scratch, it is advisable to consider making a large number of image annotations via an API or utilizing a labeling tool to expedite the process for the model.

The 47 data sets that have been labeled are further partitioned into 70% train data, 19% validation data and 11% set data, as shown in Figure 6.

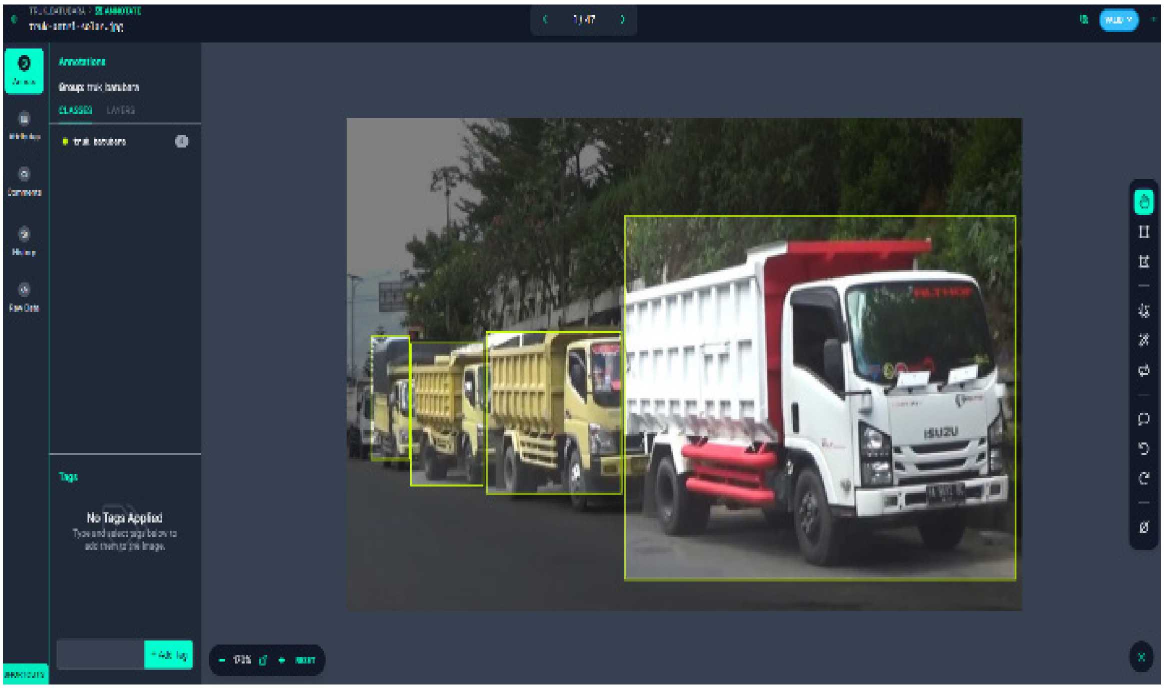


Figure 5. Dataset labeling process

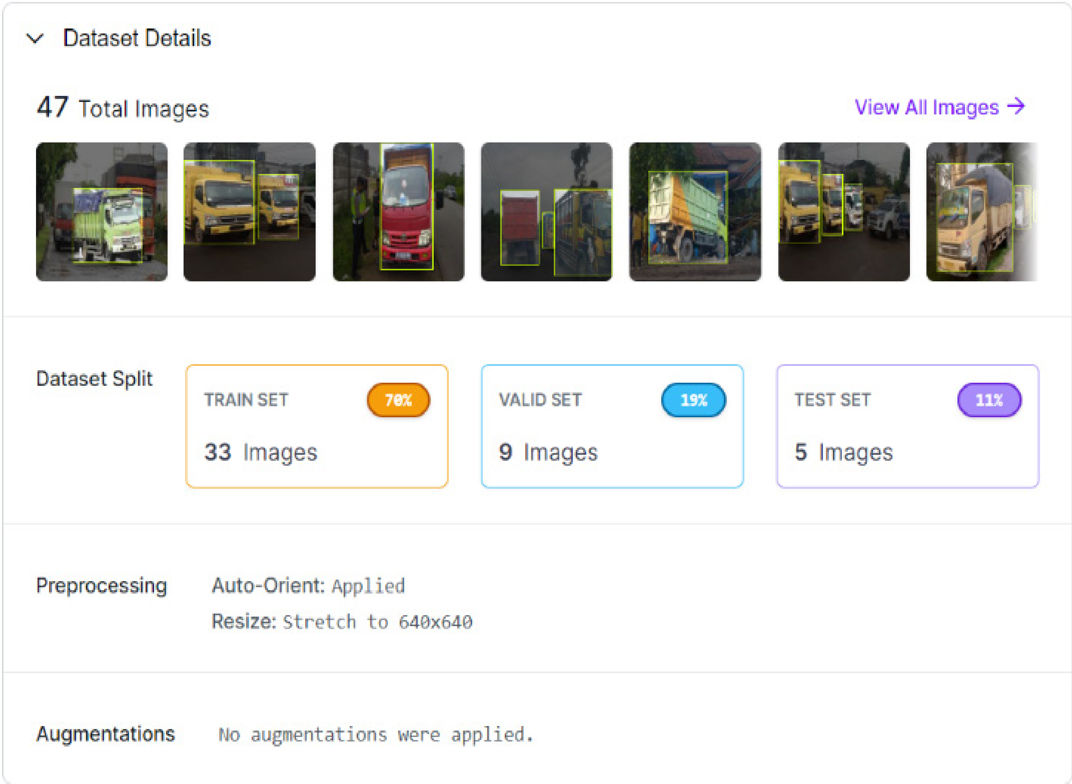


Figure 6. Roboflow's ability to maintain previous versions of the dataset

Furthermore, Roboflow has the capability to create augmented images, ensuring that the original dataset remains intact, as augmentation occurs in the final step before the dataset is utilized for training (Figure 6). Additionally, Roboflow can rename entire classes during the preprocessing phase, enabling users to either exclude them entirely or rename them as necessary [19]. In the context of this research, multiple annotators are employed, health checks are utilized to monitor annotations, and preprocessing tools are employed for adjusting classes as part of feature selection to optimize datasets for training [20].

2.1.3. Yolov9 Model Training

The prevailing approach to object detection often underscores the development of intricate network architectures or the formulation of specific-purpose functions. Nonetheless, such approaches tend to overlook a pivotal concern: The significant loss of data information during propagation across network layers. YOLOv9, an object detection model, introduces the notion of Programmable Gradient Information (PGI) to tackle the issue of information loss during data propagation across deep networks, as shown in Figure 7.

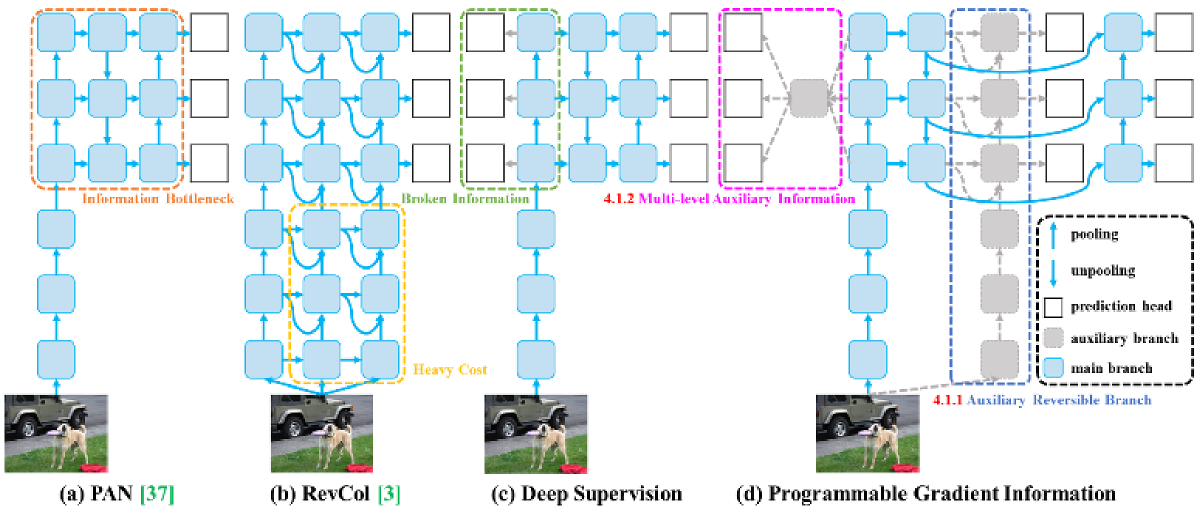


Figure 7. PGI and related network architectures and methods. (a) PAN, (b) inverted column (RevCol), (c) conventional deep supervision, and (d) PGI that was proposed [18]

PGI primarily comprises three constituents:

(1) The primary branch, which serves as the architecture employed for inference,

(2) An additional reversible branch, responsible for generating dependable gradients to supplement the primary branch for reverse propagation, and

(3) Multi-level supplementary information, governing the primary branch's assimilation of semantic information that may be stratified across multiple levels.

PGI facilitates the comprehensive preservation of input information requisite for computing the target function, thereby ensuring the provision of dependable gradient information for updating network weights.

Furthermore, the model introduces a novel lightweight network architecture (Figure 8), dubbed the Generalized Efficient Layer Aggregation Network (GELAN), grounded in gradient path planning. This architecture is engineered to optimize parameter efficiency and surpass extant methodologies in terms of parameter utilization, even employing conventional convolution operators indiscriminately across various inference devices.

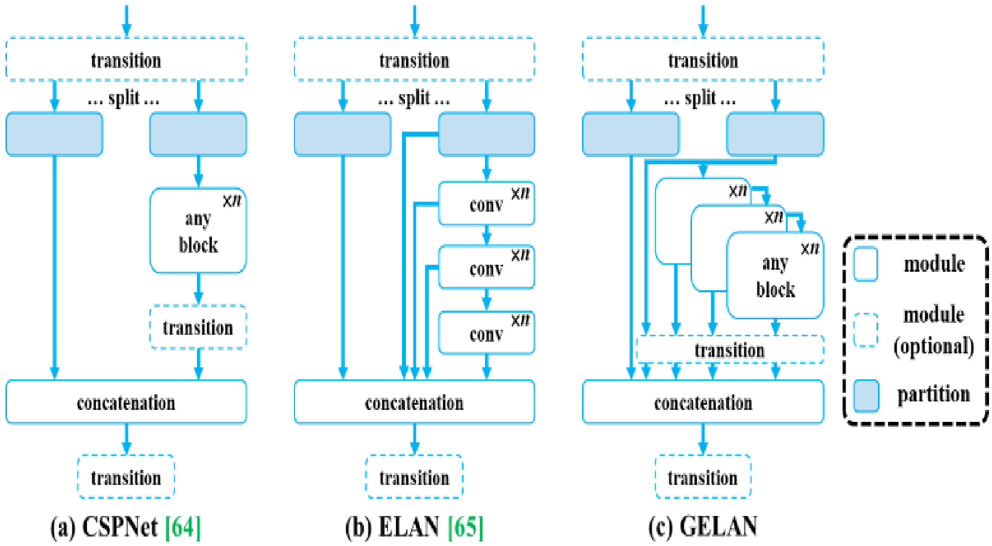


Figure 8. GELAN architecture: (a) CSPNet, (b) ELAN, and (c) GELAN implemented in YOLOv9

The proposed model and architecture are validated on the MS COCO dataset for object detection, demonstrating the ability to achieve better results than advanced trained models with large datasets, even those trained from scratch.

2.1.4. Model Evaluation

The measurements used to evaluate the performance of the first model, employing the confusion matrix, consist of accuracy, precision, recall, and F1-score. True prediction values are included in the precision class, where the actual prediction value is related to the class (category), while the overall prediction is termed accuracy. Mean values of each precision and recall class are taken to produce the overall classifier.

Accuracy: It is calculated as the number of positively predicted instances divided by the total number of instances, representing the percentage of accurately predicted values among all values. Accuracy values range from 0 to 100.

Precision: Precision is a measure of positive prediction value, calculated as the instances with class x divided by the total classified instances. High precision values indicate accurate results, implying a low rate of selecting unrelated items.

Recall: It reflects the sensitivity of the problem, indicating the quality and completeness of the product. In essence, recall denotes the proportion of relevant elements retrieved from a given set or the number of related objects selected.

The equations used to calculate accuracy, precision, recall, F1 score, and MSE are presented in Table 1, where 'n' represents the amount of data. The results of this analysis help in selecting the model that best suits a particular need.

Table 1. Performance evaluation metrics

/Metrics	Formula
Accuracy (acc)	$\frac{tp + tn}{tp + fp + tn + fn}$
Precision (p)	$\frac{tp}{tp + fp}$
Recall (R)	$\frac{tp}{tp + fn}$
F-score (F1)	$\frac{2 * p * r}{p + r}$
Root Mean Square Error (RMSE)	$\frac{(y_i - \hat{y_i}\ )^{1/2}}{n}$ Where: y_i = value of observation results $\hat{y_i}$ = predicted value i = order of data in the dataset n = number of data

3. Result

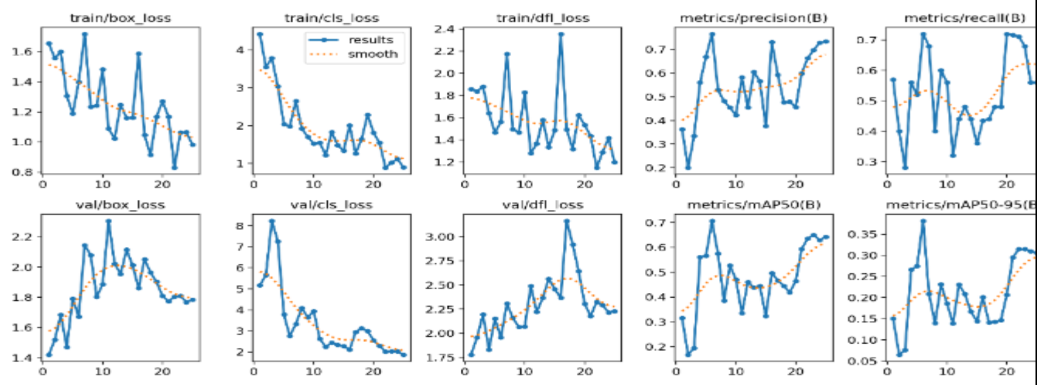
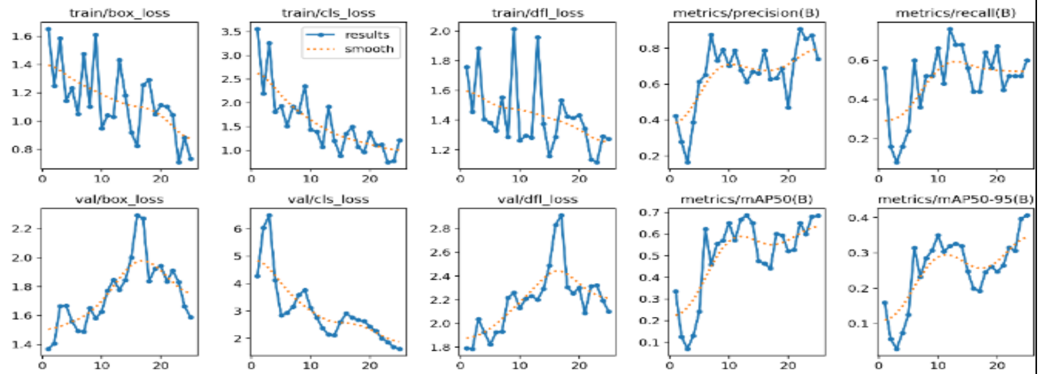
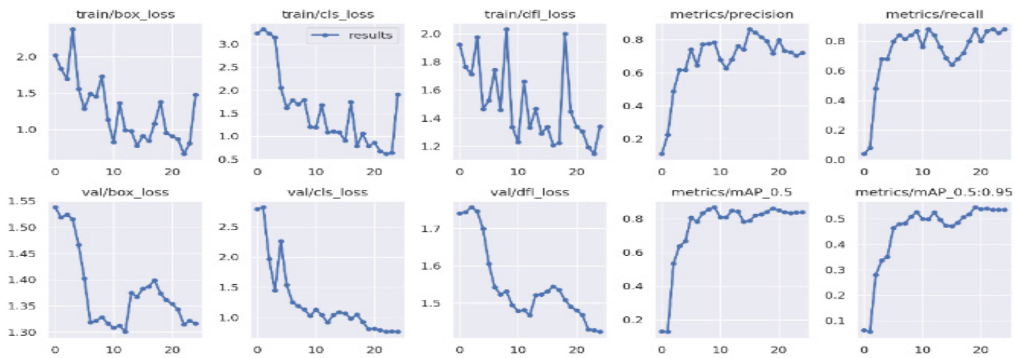
The training results are depicted graphically using three models: YOLOv8, YOLO-NAS, and YOLOv9 presented in Table 2. In terms of box_loss, the YOLOv9 model initially exhibits a decline, which stabilizes towards the end of the training epoch, particularly in cls_loss.

Early stages of val/cls_loss indicate the model's adaptation to validation data, leading to variable predictions. As adaptation progresses, smoother trends emerge, as indicated in Table 3. Throughout the training process, all models undergo changes based on metrics measured across 25 epochs, as listed in Table 3.

Table 2. Model implementation results

Model	Model Implementation Results
YOLOv8	
YOLO-NAS	
YOLOv9	

Table 3. Training model performance parameter graph

Model	Performance Parameters Graph
YOLOv8	
YOLO-NAS	
YOLOv9	

At epoch 25 of training the YOLOv8 model, the model loss value continues to decrease. The "box_loss" measures the difference between the model prediction and the object's location on the original image. It is 0.981, higher than the final value of the YOLO-NAS model, which is 0.734, and the highest among other models, YOLOv9, which is 1.478. The "class_loss" measures the error of the model in detecting an object. The end value for the YOLOv8 model is 0.896, while for YOLO-NAS, it is 01.215, and for YOLOv9, it is 1.905. Precision describes how accurately the model recognizes an object. For YOLOv8, it is 0.56, for YOLO-NAS, it is 0.6, and for YOLOv9, it is 0.88.

Recall represents the model's ability to recall the size of an object. For YOLOv8, it is 0.641, for YOLO-NAS, it is 0.649, and for YOLOv9, it is 0.83. The mAP50 value describes the overall performance of the model using a 50% IOU threshold. For YOLOv8, it is 0.305, for YOLO-NAS, it is 0.406, and for YOLOv9, it is 0.535. The MAP50-95 score emphasizes the model's ability in a stricter detection scenario, with a 50% to 95% range of IOUs.The test results of the three models indicate that YOLOv9 provided better and more detailed predictions for labeling image datasets compared to YOLOv8 and YOLO-NAS (refer to Figure 9). Specifically, the YOLOv8 model correctly identified coal-carrier truck objects 20 times, as illustrated in Figure 9a, Figure 9b, and Figure 9c.

(a)

(b)

(c)

Figure 9. (a) The result of model prediction labeling on yolov8;
(b) yolonas; (c) yolov9

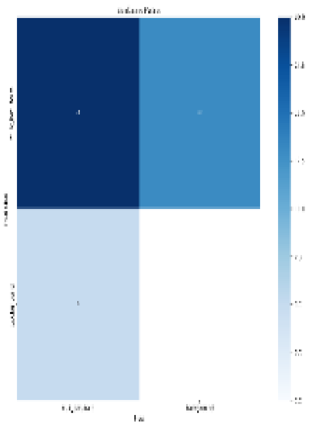
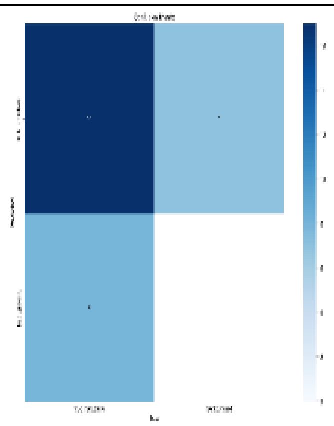
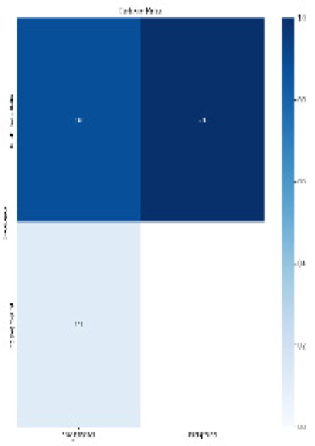
The YOLO-NAS model successfully detected coal carrier trucks 17 times while YOLOv9 detected coal carrier truck 41 times. The performance metrics for the YOLOv8 model are presented in Table 4 and Table 5: F1 score of 0.74, Recall value of 0.707, and accuracy value of 0.707. These metrics indicate satisfactory performance for the model.

On the other hand, the YOLO-NAS model achieved F1 score of 0.66, a recall value of 0.94, and a precision value of 0.685. The implementation of the YOLOv8, YOLO-NAS, and YOLOv9 models demonstrated that the best results for object detection of barrier trucks in video detail are depicted in Figure 9.

Table 4. Comparison value of training on models

Model	**YOLOv8**	**YOLO-NAS**	**YOLOv9**
Epoch	25	25	25
ox_loss	0.981	0.734	1.478
cls_loss	0.896	1.215	1.905
Precision	0.56	0.6	0.88
Recall	0.641	0.684	0.839
mAP_0.5	0.305	0.406	0.535
mAP50-95	1.784	1.588	1.316

Table 5. Confusion matrix

YOLOv8	**YOLO-NAS**	**YOLOv9**
		

It can be seen in Table 6 that the YOLOv8 model shows that from the results of object detection, the coal transport truck identified coal truck objects 17 times. Furthermore, the YOLOv9 model succeeded in identifying 41 coal truck objects. it correctly 20 times, meaning that this model was successful in identifying the object of the coal transport truck. The YOLO-NAS model succeeded in detecting.

Table 6. Comparison chart of model performance results

Model	**F1**	**Recall**	**Precision**
YOLOv8	0.74	0.707	0.707
YOLO-NAS	0.66	0.94	0.685
YOLOv9	**0.79**	**1.00**	**0.862**

3. Discussion

This research successfully implemented and evaluated an object detection model using the YOLOv9 algorithm to improve the accuracy and reliability of coal truck detection on national transportation routes. The study followed a structured methodology that included dataset pre-processing, model training, and performance evaluation using standard metrics. The dataset, consisting of 42 samples, underwent systematic pre-processing strategies to enhance data quality and minimize noise. Subsequently, three models—YOLOv8, YOLO-NAS, and YOLOv9—were trained and evaluated. The results demonstrated that YOLOv9 consistently outperformed YOLOv8 and YOLO-NAS across multiple evaluation metrics.

Key performance metrics for YOLOv9 included, a box_loss of 1.478, a Cls_loss of 1.905, a precision of 0.88, a recall of 0.839, mAP_5.0 of 0.535, a mAP50-95 of 1.316.

Furthermore, the accuracy of the models was assessed using a confusion matrix, which confirmed that YOLOv9 displayed the highest accuracy and overall performance. The F1 score of 79% and a recall rate of 100% underscore the robustness of YOLOv9 in detecting coal trucks accurately under varying conditions. This study highlights several significant findings and implications. YOLOv9 demonstrated superior accuracy in detecting coal trucks, offering notable advantages in improving traffic safety and reducing accidents through precise and reliable detection. Its real-world applicability spans traffic surveillance, logistics management, and real-time monitoring systems, making it a versatile tool for transportation safety. From a technical perspective, the research underscores the importance of data pre-processing and parameter optimization in enhancing model performance. However, despite its strengths—such as high accuracy, effective data handling, and practical real-time applicability—the study also reveals some shortcomings, including limited dataset size, untested environmental variability, and high computational demands during training and deployment.

Looking ahead, future research should focus on expanding dataset diversity, conducting real-time deployment testing, integrating YOLOv9 with IoT and edge computing platforms, adapting the model to varied environmental conditions, and exploring hybrid detection models to further improve accuracy and efficiency.

These directions aim to maximize the potential of YOLOv9 for more reliable and scalable applications in coal truck monitoring systems.

4. Conclusion

This study investigated the application of the YOLOv9 algorithm to improve the detection of coal trucks on national transportation routes, addressing critical challenges in coal transportation logistics and safety. Through a structured methodology, including dataset preparation, model training, and rigorous performance evaluation, the study demonstrated the superior capabilities of YOLOv9 in detecting coal trucks under diverse conditions. The research compared three models—YOLOv8, YOLO-NAS, and YOLOv9—and highlighted YOLOv9's outstanding performance with an F1 score of 79%, a perfect recall rate of 100%, and enhanced precision at 88%. The study's findings underscore the potential of advanced deep learning techniques to enhance real-time monitoring systems.

YOLOv9's innovative features, such as Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN), enable the model to mitigate data loss during propagation and optimize parameter utilization. These advancements allow YOLOv9 to deliver high accuracy and efficiency, making it suitable for critical applications in transportation safety, logistics management, and traffic monitoring. The implementation of such systems can reduce traffic accidents, optimize resource allocation, and improve overall safety in coal transportation operations.

The study demonstrates significant benefits, including enhanced detection accuracy and reliability in challenging environments, showcasing YOLOv9 as a viable solution for modern transportation safety systems. Its application extends beyond coal truck detection, offering potential use cases in broader logistics and traffic surveillance domains. Furthermore, the integration of advanced algorithms like PGI and GELAN highlights the importance of innovative approaches in overcoming traditional limitations of object detection models.Despite its promising results, the study faced limitations. The relatively small dataset size restricted the model's training scope, potentially limiting its generalizability to more diverse or complex scenarios. Additionally, the computational demands of YOLOv9 pose challenges for real-time deployment in resource-constrained environments. Environmental factors, such as varying weather conditions, lighting, and road infrastructure, were not extensively explored, leaving gaps in assessing the model's adaptability.

Future research should focus on addressing the identified limitations. Expanding the dataset to include a wider variety of scenarios and environments would enhance the model's robustness and generalizability. Exploring lightweight implementations of YOLOv9 for deployment on edge devices or IoT platforms could enable real-time applications in constrained settings.

Furthermore, hybrid detection approaches that combine YOLOv9 with other machine learning models or sensor data could improve accuracy and adaptability in dynamic environments. Investigating solutions to reduce the computational complexity of the model without sacrificing performance would also be a valuable contribution to the field.In conclusion, this study provides a foundation for utilizing YOLOv9 in coal truck detection and highlights its potential for broader applications in intelligent transportation systems. By addressing the limitations and exploring the suggested future research directions, YOLOv9 can be further optimized to drive advancements in safety, efficiency, and sustainability in transportation and logistics.

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