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Optimizing Road Safety with MobileNet-Based Classification of Over-dimensioned Trucks

Nurul Afifah Arifuddin[1], Hary Capri[2], Deni Setiawan[3], Rifka Dwi Amalia[4], Kharisma Wiati Gusti[5]
[1,2,4,5]Universitas Pembangunan Nasional Veteran Jakarta, Jl. Rs. Fatmawati Pondok Labu Jakarta, 12450, Indonesia
[3]Jasamarga, Plaza Tol Taman Mini Indonesia Indah Jakarta, 13550, Indonesia

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Abstract – *This study aims to automatically detect overdimension trucks using a lightweight and efficient deep learning model based on MobileNet. Overdimension trucks pose serious threats to road infrastructure, traffic safety, and contribute to increased economic costs due to road damage and congestion. The developed model utilizes MobileNet as a feature extractor without the standard fully connected layers, and is equipped with additional layers including Flatten, Batch Normalization, Dense with Leaky ReLU activation, and Dropout to enhance training stability and prevent overfitting. The dataset consists of two classes—normal trucks and overdimension trucks—with images sized 128×128 pixels, collected from internet sources and field photos. The training process employs binary crossentropy loss, the Adam optimizer with an initial learning rate of 0.0001, and an Early Stopping mechanism. Fine-tuning is performed by unfreezing layers from the 100th layer upward and lowering the learning rate to 0.00001. Evaluation results show an accuracy of 97.92%, with consistent loss and accuracy visualization, demonstrating the model's capability in classifying overdimension trucks to support automatic traffic monitoring systems. This model has the potential to be implemented in toll gate systems to automatically deny access to overdimension vehicles. Furthermore, integration with roadside CCTV allows real-time monitoring of vehicle dimension violations across various traffic checkpoints.*

Keywords: *Overdimension, Truck, Deep Learning, Mobilenet, Classification*

Corresponding Author:

Nurul Afifah Arifuddin

Email:

nurulafifaharifuddin@upnvj.ac.id

Abstrak – *Penelitian ini bertujuan untuk mendeteksi truk overdimensi secara otomatis menggunakan model deep learning berbasis MobileNet yang ringan dan efisien. Truk overdimensi memberikan dampak serius terhadap infrastruktur jalan, keselamatan pengguna jalan, dan meningkatkan biaya ekonomi akibat kerusakan jalan dan kemacetan. Model yang dikembangkan menggunakan MobileNet sebagai feature extractor tanpa lapisan fully connected standar, dan dilengkapi dengan lapisan tambahan berupa Flatten, Batch Normalization, Dense dengan aktivasi Leaky ReLU, serta Dropout untuk meningkatkan stabilitas pelatihan dan mencegah overfitting. Dataset terdiri dari dua kelas, yaitu truk normal dan truk overdimensi, dengan citra berukuran 128×128 piksel yang dikumpulkan dari sumber internet dan foto lapangan. Proses pelatihan menggunakan binary crossentropy loss, Adam optimizer dengan learning rate awal 0,0001, dan mekanisme Early Stopping. Fine-tuning dilakukan dengan membuka layer ke-100 ke atas serta menurunkan learning rate menjadi 0,00001. Evaluasi menunjukkan akurasi 97,92%, dengan visualisasi loss dan akurasi yang konsisten, membuktikan kemampuan model dalam klasifikasi truk overdimensi untuk mendukung sistem monitoring lalu lintas otomatis. Model ini berpotensi diimplementasikan pada sistem gerbang tol untuk menolak akses kendaraan overdimensi secara otomatis. Selain itu, integrasi dengan CCTV jalan raya memungkinkan pengawasan real-time terhadap pelanggaran dimensi kendaraan di berbagai titik lalu lintas.*

Kata Kunci*: Truk, Overdimensi, Deep Learning, MobileNet, Klasidikasi*

I. INTRODUCTION

The issue of over-dimensioned trucks in Indonesia remains unresolved and continues to pose a significant challenge for transportation authorities. The high prevalence of vehicles exceeding standard size and weight limits underscores the urgent need for stricter monitoring and more efficient enforcement strategies. Despite various regulatory efforts, enforcement remains hindered by factors such as pressure from the logistics industry and drivers' perceptions of inconsistent implementation on the ground.

Over-dimensioned trucks have a substantial negative impact on multiple aspects of transportation infrastructure, road safety, and national economic sustainability. Their excessive weight and size exert stress beyond the design capacity of roads and bridges, accelerating deterioration and increasing the risk of structural failure. A notable example is the collapse of the Widang Bridge in Tuban, East Java, in 2018, which occurred after it was traversed by an overloaded truck [1].

Prior studies support these concerns. Budiharjo et al. revealed that over-dimensioned vehicles contribute significantly to infrastructure degradation and heightened accident risks [2]. Overloading impairs optimal braking performance, making it difficult for drivers to maintain control, especially on steep slopes and sharp curves [3]. Gunawan et al. further highlighted that trucks with excessive dimensions suffer from reduced stability and maneuverability, increasing the likelihood of traffic accidents [4].

Pratama et al. emphasized the importance of adopting technology-based monitoring systems to replace manual inspection methods, which are often slow, labor-intensive, and error-prone. Their study supported the implementation of Weight in Motion (WIM) technology to detect violations in real-time [5]. While WIM and similar systems improve efficiency, they still rely heavily on physical sensors and infrastructure investment, limiting their scalability in widespread or remote areas.

Meanwhile, deep learning-based approaches have gained traction as a viable alternative due to their potential for automation and accuracy. Cil et al. employed MobileNet to detect road surface conditions using roadside imagery, demonstrating the model's high speed and reliability for image-based detection tasks [6]. Wang et al. compared the performance of object detection algorithms such as SSD and YOLO with different backbones, including MobileNetV2, and found that model performance varies significantly based on architectural choices [7]. Sun et al. proposed a lightweight truck detection system using YOLOv5s with a MobileNetV3 backbone, showing that such architectures are well-suited for real-time applications on embedded devices [8].

However, many of these existing solutions have notable limitations. Most of them focus on general vehicle detection or weight estimation, rather than specifically classifying vehicles based on their dimensions. Additionally, they often require high computational resources or rely on supplementary hardware such as LiDAR, GPS, or infrared sensors, which increases deployment complexity and cost. These dependencies make such systems less practical for large-scale, real-time implementation, especially in roadside environments with limited infrastructure or connectivity.

Although recent work by Afifah et al. demonstrated the use of CNNs for over-dimensioned truck detection using image data alone, their model still relied on relatively general convolutional layers [9]. Another study applied MobileNet SSD for object detection with strong results, reinforcing the potential of MobileNet-based architectures in edge computing environments [10]. These studies collectively demonstrate that lightweight convolutional models offer high detection accuracy while minimizing computational demands, making them suitable for large-scale deployment.

This research contributes a practical and cost-efficient solution to the problem of over-dimensioned truck monitoring by proposing a system designed for seamless integration into existing infrastructures. The model enables real-time alerts through roadside electronic displays, supports automated gate control at toll booths or bridge access points to restrict access for violating vehicles, and allows for violation logging with integration into electronic ticketing systems (e-ticketing), thereby enhancing enforcement efficiency and road safety.

This research contributes a practical and cost-efficient solution to the problem of over-dimensioned truck monitoring. The system is intended for seamless integration into existing infrastructures, such as: Real-time alerts via roadside electronic displays; Automated gate control at toll booths or bridge access points; and violation logging and integration with electronic ticketing systems (e-ticketing). By enabling accurate and automated detection, this model supports the Zero ODOL (Over Dimension Over Load) policy and enhances public safety, traffic efficiency, and long-term infrastructure sustainability.

II. METHOD

A. Data preparation

The dataset used in this study was prepared using a hybrid method, combining images sourced from the internet with additional photographs taken by the researchers using standard smartphone cameras. The internet-sourced images were collected from publicly accessible platforms such as transportation-related websites, news archives, and open-source image repositories, ensuring a diverse range of truck types and road conditions. To enhance the dataset and include more realistic scenarios, supplementary images were captured directly on-site at selected highway locations using smartphone cameras. This allowed for the inclusion of various environmental conditions, such as different lighting, angles, and backgrounds. All images were manually labeled into two categories: over-dimensioned trucks and normal trucks. The use of a hybrid dataset approach increased the diversity and robustness of the training data, supporting the model's ability to generalize effectively in real-world conditions.

The dataset used in this study consisted of a total of 236 images, comprising 118 over-dimensioned trucks and 118 normal trucks. A hybrid data collection approach was employed, where part of the data was sourced from publicly available internet platforms, and the rest was captured by the researchers using standard smartphone cameras at selected highway locations. All images were manually labeled into two categories: over-dimensioned and normal trucks.

For the model development process, the dataset was divided into two parts: 80% for training and 20% for validation, following a stratified split to maintain class balance. This resulted in 188 images for training (94 over-dimensioned, 94 normal) and 48 images for validation (24 over-dimensioned, 24 normal). An additional 9 images were used for testing purposes, which were completely separate from the training and validation sets to evaluate the model's performance on unseen data. This structured data split aimed to ensure the robustness of the training process while providing a reliable evaluation of the model's generalization ability.

B. Data Preprocessing

The dataset used in this study consists of two classes: normal trucks labeled as 0 can be seen for example in figure 1 and overloaded trucks labeled as 1 can be seen in figure 2.

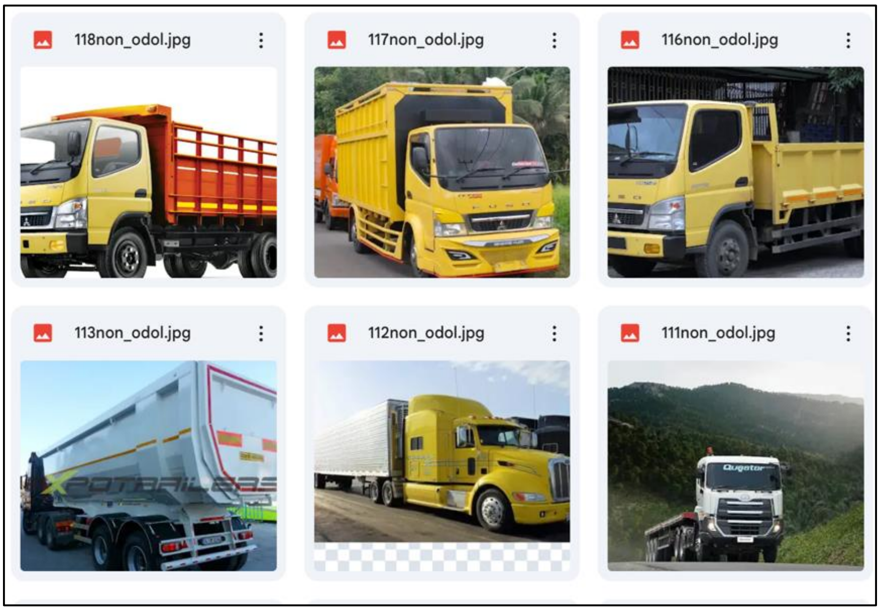

Figure 1. Normal truck example

Each image in the dataset was resized to 128x128 pixels to maintain uniformity during the training process. The pixel values were also normalized by dividing them by 255.0, converting the range to values between 0 and 1.

To ensure consistency in accuracy across experiments, a seed was set. By using a fixed seed, all random operations, such as weight initialization, data augmentation, and shuffling, follow the same sequence, allowing the model's results to be reproducible and comparable under similar conditions [11].

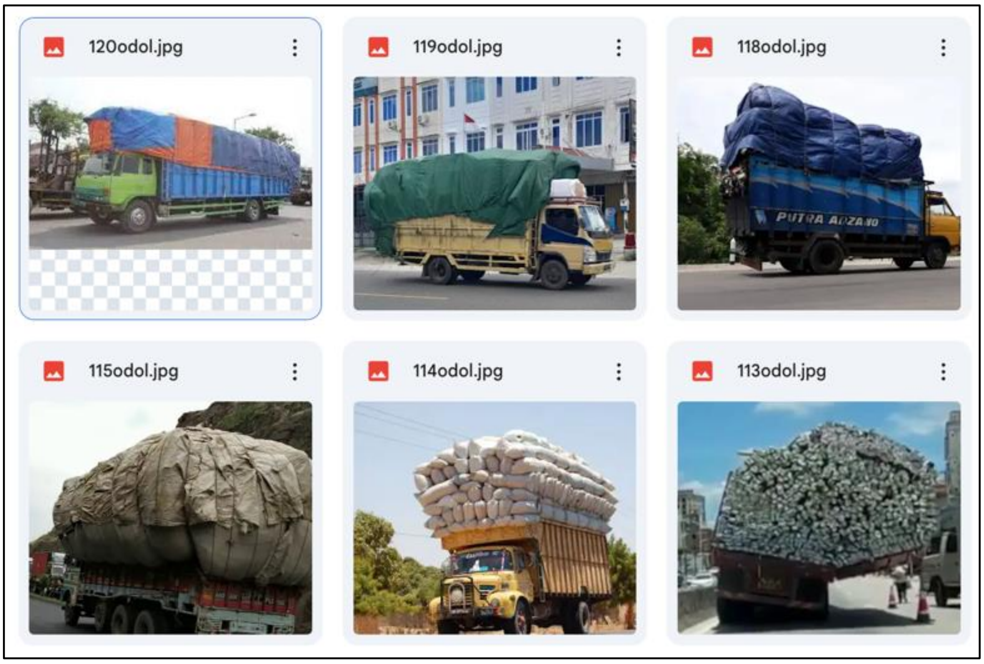

Figure 2. Over-dimension Truck Example

In addition, data augmentation was applied to the training dataset to increase the diversity and variability of images used during model training. The augmentation techniques included random rotation (±15 degrees), horizontal and vertical shifts (up to 10% of image dimensions), zooming (range 0.9 to 1.1), and horizontal flipping. These transformations were designed to simulate real-world variations in image capture, such as different viewing angles, object positions, and distances. By introducing these augmentations, the model was expected to become more robust and generalizable to unseen data, reducing the risk of overfitting and improving performance in practical applications. This approach is expected to enhance the model's performance in detecting over-dimensioned trucks more accurately [12], [13].

C. Model Architecture

The model architecture in this study utilizes MobileNet as a feature extractor without including the standard top (fully connected) layer. The MobileNet used is a transfer learning model pre-trained on the ImageNet dataset to accelerate the training process by leveraging pre-trained weights. In the initial training stage, all layers of the MobileNet base model were frozen to keep the weights fixed and prevent overfitting [14]. By freezing these layers, the model only trains the additional layers specifically designed to detect over-dimensioned trucks.

The additional layers on top of the MobileNet architecture consist of several key components. First, the Flatten layer is used to flatten the feature maps so they can be fed into the fully connected layers [15]. Next, a Batch Normalization layer is added to maintain training stability by normalizing activations for each batch, making the training process more stable and ensuring faster convergence. Afterward, a Dense layer with 64 units and a Leaky ReLU activation function is used to process the flattened features. The Leaky ReLU activation function was chosen because it can handle negative values while still retaining their contributions during the learning process [16].

To prevent the model from relying too heavily on specific weights and to reduce the risk of overfitting, a dropout **l**ayer with a 50% rate is applied. According to a study by Cai et al., dropout is a regularization technique that randomly deactivates units (neurons) during training to prevent them from becoming overly dependent on each other [17]. This approach improves the model's generalization ability by reducing overfitting.

At the output layer, a single neuron with a sigmoid activation function is used to produce an output in the form of probabilities. This activation function is suitable for binary classification tasks, which in this study aim to distinguish between normal trucks and over-dimensioned trucks. This architecture is expected to provide optimal performance in classifying over-dimensioned and non-over-dimensioned trucks accurately and efficiently.

The overall architecture described above is illustrated in Figure [X], which visually represents the flow of data through the model. As shown in the diagram, the input image is first processed by the MobileNet base model, where feature extraction is performed with all layers initially frozen. The extracted features are then passed sequentially through the Flatten layer, Batch Normalization, Dense layer with Leaky ReLU activation, and a Dropout layer with a rate of 0.5. Finally, the Output layer, consisting of a single neuron with a Sigmoid activation function, provides a probabilistic classification result. This diagram helps to clarify the modular structure of the model and how each component contributes to the overall classification task.

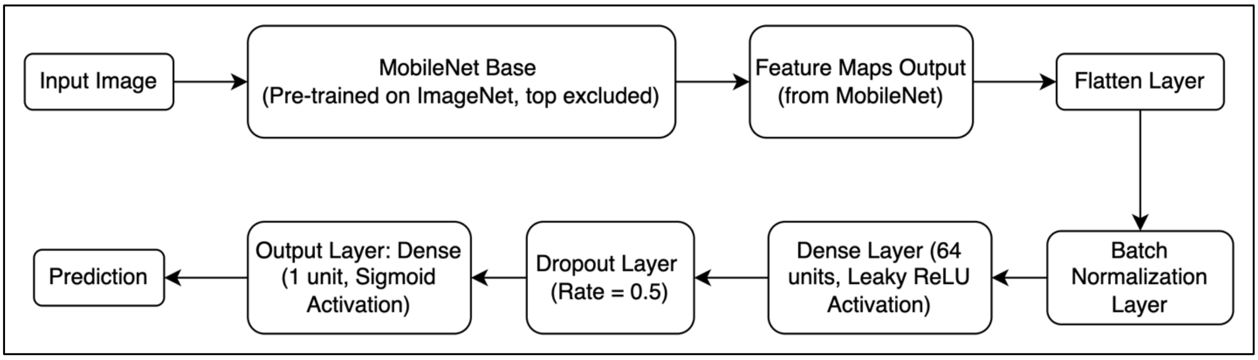

Figure 3. Mobile-net Architecture

III. RESULT AND DISCUSSION

The model training process utilized the binary cross entropy loss function and the Adam optimizer with an initial learning rate of 0.0001. The training was conducted over 50 epochs and included an Early Stopping callback to halt the training if there was no improvement in the validation loss for five consecutive epochs. Additionally, a Learning Rate Scheduler was used to adjust the learning rate exponentially to ensure a more stable training process and faster convergence.

After the initial training was completed, a fine-tuning process was performed by unfreezing the layers from the 100th layer onward, allowing the weights in these layers to be updated during retraining. This step was aimed at enhancing the model's ability to extract specific features relevant to the dataset. During the fine-tuning stage, the learning rate was reduced to 0.00001 to maintain stable weight updates and prevent drastic changes that could lead to the loss of previously learned knowledge. The retraining process was conducted over 10 epochs to maximize the model's accuracy without causing overfitting.

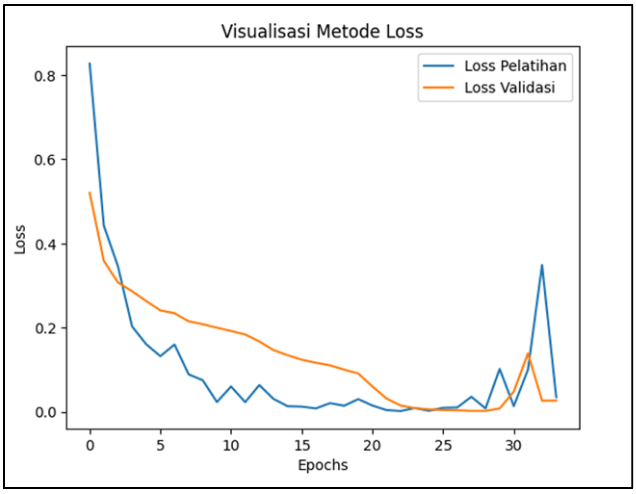

Figure 4. Loss Training and Validation

The model evaluation was conducted using the test data to measure the model's performance in detecting over-dimensioned trucks. The evaluation results showed an accuracy of 97.92%, indicating the model's effectiveness in correctly classifying truck images. In addition to accuracy measurement, the model also provided visualizations in the form of graphs to monitor the training and validation process.

The training results were visualized using a **loss graph** (as shown in Figure 1) and an **accuracy graph** (as shown in Figure 2). The loss graph illustrates changes in the loss value during training and validation, while the accuracy graph depicts the model's accuracy on the training and validation data as the number of epochs increases. Based on the visualization of the loss and accuracy graphs, the model did not exhibit signs of overfitting, as the loss and accuracy values for both training and validation datasets demonstrated similar and consistent patterns. Early stopping occurred at approximately epoch 32 during the fine-tuning phase, when no improvement in validation loss was observed over several consecutive epochs. The loss curve began to stabilize after fine-tuning, specifically around epoch 25, indicating that the model had reached convergence without significant fluctuations. These visualizations help in understanding whether the model experienced overfitting or underfitting during the training process.

In addition to the accuracy and loss metrics, a confusion matrix that can be seen in Figure 6, was used to further evaluate the classification performance of the model. The confusion matrix results showed that the model successfully identified 25 normal trucks (true negatives) and 22 over-dimensioned trucks (true positives), with only 1 over-dimensioned truck misclassified as normal (false negative), and no false positives. These results yielded a precision of 1.0000 and a recall of 0.9565 for the over-dimensioned class, resulting in an F1-score of 0.9778. This high performance across all key classification metrics confirms that the model is not only accurate but also reliable in detecting critical ODOL (Over Dimension Over Load) cases, which is essential for real-world deployment in intelligent traffic monitoring and enforcement systems.

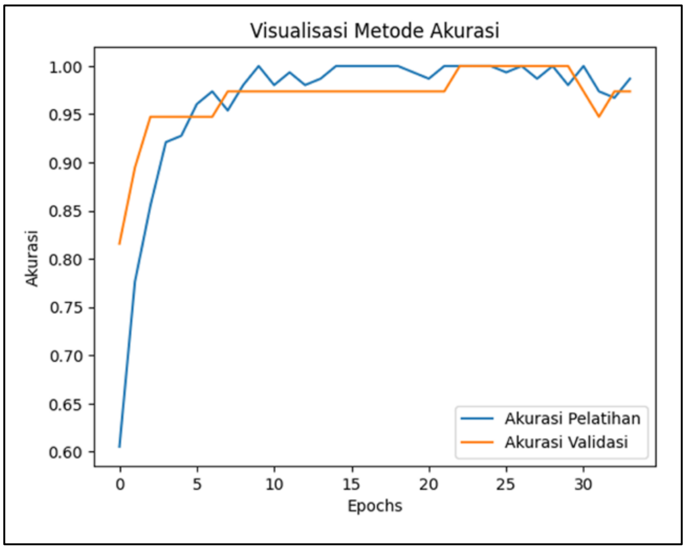

Figure 5. Training and Validation Accuracy

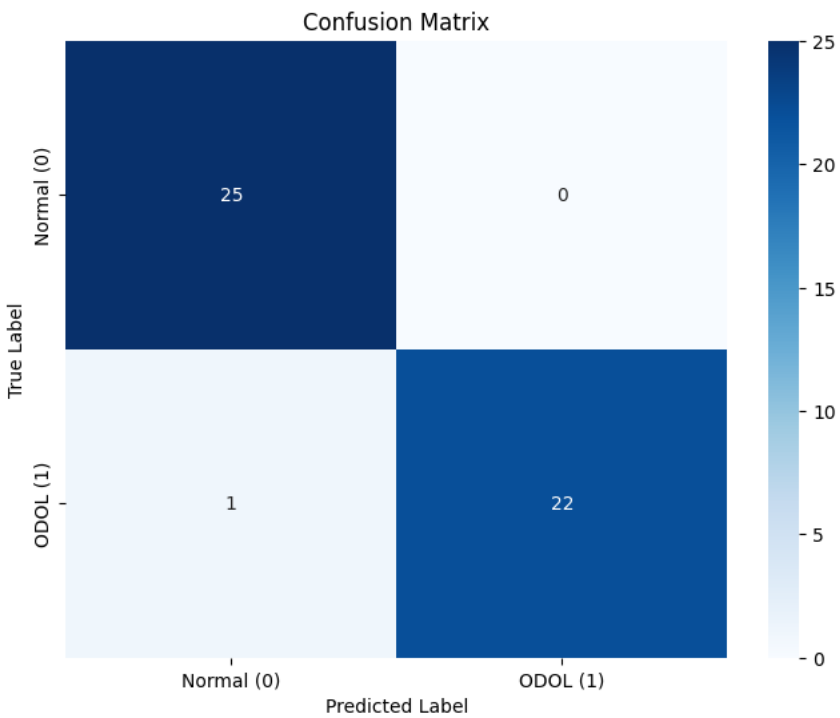

Figure 6. Confusion Matrix of Odol Truck Classification

Figure 7. Visualization of Overdimensioned and Non-Overdimensioned Truck Classifications

In addition to numerical evaluations and graphs, the model also made predictions on several truck images that had not been used during the model development process. The prediction results were displayed in a grid format along with labels indicating the classification probabilities. If the prediction probability was ≥ 0.6, the truck image was classified as overload. If the probability ranged between 0.4 and 0.6, the classification result was labeled as Not Sure. Meanwhile, if the probability was < 0.4, the truck was classified as not overload. This approach provides a clear guideline for assessing the accuracy of the model's predictions.

Predictions falling between 0.4 and 0.6 were considered within an uncertain range. This strategy is commonly applied in CNN-based classification systems to balance prediction accuracy with model uncertainty, as demonstrated in prior studies. Moreover, this approach allows for the interpretation of ambiguous prediction results, thereby enhancing the reliability of the system in image-based decision-making contexts. [18]

IV. CONCLUSION

This study successfully developed an over-dimensioned truck detection model based on MobileNet with an accuracy of 97.92%. The use of MobileNet as a transfer learning architecture proved effective in producing an accurate model despite operating with limited computational resources. The fine-tuning process enhanced the model's ability to recognize specific features relevant to the dataset. In addition to numerical evaluation results, the visualizations of the training and validation processes indicated that the model did not experience overfitting. The implementation of this model can support automated monitoring on highways, reduce the potential for human error, and improve the efficiency of over-dimensioned truck monitoring.

However, this research also has several limitations. The model was trained and tested on a relatively limited dataset, which may affect its generalization capability in more diverse real-world conditions, such as variations in camera angle, lighting, and background. In addition, although MobileNet offers advantages in speed and efficiency, it may have limitations in capturing more complex spatial features compared to heavier architectures. The current implementation also focuses solely on classification, without integrating real-time detection or localization components that are essential for dynamic traffic monitoring systems.

For future research, it is recommended to explore the use of more advanced architectures such as EfficientNet, ResNet, or YOLO, which may offer improvements in detection accuracy, processing speed, or feature representation. Expanding the dataset with more varied truck images and implementing advanced hyperparameter optimization techniques could further improve the model's robustness and adaptability across different highway monitoring scenarios. Integrating the model into a real-time detection system with warning mechanisms or automated access control (e.g., toll gates) can also be explored as the next development phase.

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