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Research Article

Intelligent Traffic Light System Using Convolutional Neural Network to Optimize Vehicle Flow in Indonesia

Bhustomy Hakim[1], Fergie Joanda Kaunang[2], Yemima Monica Geasela[1] and Regina Hillary[2]

[1]*Department of Information Systems, Bunda Mulia University, Jakarta, Indonesia*
[2]*Department of Informatics, Bunda Mulia University, Jakarta, Indonesia*

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Corresponding Author:
Bhustomy Hakim, Bunda Information System, Universitas Bunda Mulia, Indonesia
Email: bhustomy.hakim@gmail.com

Abstract: Traffic congestion remains a persistent challenge in major Indonesian cities due to rapidly increasing vehicle density and the continued reliance on fixed-time traffic signal scheduling. This study aims to develop an intelligent traffic light system that dynamically adjusts sequencing based on real-time road conditions. A dataset of 902 CCTV images was collected from intersections in six large cities across Indonesia, including Jakarta, Bandung, Surabaya, Medan, Bali, and Samarinda, and labeled into three density categories (low, medium, high). To classify vehicle density, two Convolutional Neural Network (CNN) architectures were designed and trained, incorporating preprocessing techniques such as image resizing, color inversion for illumination normalization, and data augmentation to enhance generalization. The performance of the CNNs was compared against a fuzzy logic model and a YOLOv8-based detection pipeline. Evaluation using stratified 10-fold cross-validation showed that the second CNN architecture achieved the best performance with an accuracy of 81%, precision of 0.87, recall of 0.83, and F1-score of 0.849, outperforming both baselines. Ablation studies further demonstrated that batch normalization, dropout, and data augmentation significantly reduced overfitting and improved robustness across varying light conditions. These findings indicate that a lightweight, global-context CNN can provide reliable density classification and serve as the decision engine for adaptive traffic light control. Future work will expand dataset diversity, test cross-city generalization, and explore real-time deployment in collaboration with transportation authorities to support smart city development in Indonesia.

Keywords: Intelligent Traffic Light, Traffic Flow, CNN, Deep Learning, Decision Support System

Introduction

Indonesia is the fourth most populous country in the world, with 283 million citizens, and a significant percentage of its population is concentrated in major urban areas. While this demographic concentration offers numerous opportunities, it also presents serious challenges one of which is traffic congestion (Gupta et al., 2023). Indonesia's large population naturally leads to high mobility in executing daily activities. The number of motor vehicles nationwide has grown to reach remarkably high figures. In 2022, the number of registered motor vehicles in Indonesia reached 17,168,862 cars, 243,450 buses, 5,544,173 trucks, and 125,305,332 motorcycles, resulting in a total of 148,261,817 motor vehicles nationwide (Kumalasanti and Susanti, 2024). Traffic is spread throughout the country due to congested vehicle flow in the large cities of Indonesia.

Some causes for the traffic include high vehicle density on a particular road at a time, traffic accidents on congested roads, and intersections with traffic lights, which can cause vehicles to wait and idle, resulting in increased vehicle density on the road (Nasution et al., 2023). In large Indonesian cities, red lights usually have a 30-120 second duration. The average 1-minute wait can often cause extreme traffic congestion during peak hours. Furthermore, traffic light sequencing is still managed in a fixed rotation based on the number of lanes, despite there being lanes with lower density in the intersection (Tippannavar and Yashwanth, 2023).

Technological advancements have provided support in sectors of human activities such as traffic management. Indonesia has implemented electronic ticketing cameras that identify plate numbers with traffic violation indications (Kinanti et al., 2024). In other countries, such as the United States, the implementation of intelligent traffic management systems to determine vehicle density resulted in a 50% traffic reduction (Whardana and Rentelinggi, 2024). They detected vehicle density by using real-time camera technology with a fuzzy logic model (Suwintono and Kaunang, 2022). Deep Learning later emerged, increasing and stabilizing accuracy for computer vision problems with visual imagery, such as YOLO to do segmentation and Convolutional Neural Network (CNN) (Ghawate et al., 2023). There have been smart cities that have implemented intelligent traffic management systems, but they rely on GPS to determine traffic density; therefore, they are still ineffective in overcoming traffic congestion problems (Chakir et al., 2024).

As reviewed in the Related Works section, many vision-driven systems operationalize density estimation indirectly via a sequential pipeline: object detection, counting, and thresholding. This approach is inherently brittle under conditions typical of Indonesian intersections, such as severe occlusion, nighttime glare, and the low-resolution video feed characteristic of common CCTV infrastructure. Furthermore, prior studies rarely report cross-city and day–night evaluation with stratified k-fold averages, seldom provide an ablation study to rigorously attribute performance gains (e.g., the specific contribution of BatchNorm, Dropout, Augmentation, or architectural depth), and frequently omit discussions on latency and model size crucial for practical edge deployment. These omissions significantly limit the generalization, reproducibility, and practical adoption of the proposed methodologies.

Therefore, this study presents a CNN-based model for real-time vehicle density classification using traffic imagery, designed as a core component of a Decision Support System (DSS) to dynamically prioritize traffic light sequencing based on lane congestion. This study hopes to support Indonesia in creating smart cities, implemented in major urban areas such as Jakarta, Bandung, Surabaya, Medan, Bali, and Samarinda, to represent the actual condition of Indonesia. The resulting CNN classification will act as the main engine of a decision support system that prioritizes traffic flow in real time, assisting traffic management authorities in dynamically adjusting traffic light durations based on current congestion levels.

Related Work

Technology has become one of the answers to existing problems, particularly artificial intelligence, which is able to do classification, clustering, and regression (Hakim et al., 2024). For problems in understanding image data conditions, it is possible to implement machine learning as a solution (Yanti et al., 2024). This study is faced with the challenge of developing a system that understands the conditions of an intersection in order to determine the priority of lanes that should be allowed to proceed first, based on real-time CCTV image data. In a previous international journal, Greece implemented the VISSIM algorithm on traffic lights (Zavantis et al., 2024), but was not able to reduce congestion effectively since it falls broadly into rule or simulation-based systems and vision-driven learning pipelines.

The United States has also developed traffic light technology in its smart cities using a fuzzy logic model with an accuracy of 56.75% which, when implemented, can reduce the traffic in Boston by 50% (Elassy et al., 2024). Deep Learning has emerged with the concept of a better and more stable model for computer vision problems with CNN (Zhao et al., 2024). Recent studies have compared the fuzzy logic model with the CNN model in image data processing and stated that CNN has shown enhanced accuracy with an increase of 20-35% compared to the previous model (Shao et al., 2024). A model with higher accuracy can certainly increase the performance of the decision support system that will be implemented inside the intelligent traffic management system (Hakim et al., 2024). Decision support systems function effectively if their criteria and sub-criteria can quickly adapt to changing conditions (Hakim and Fendyanto, 2022). In that instance, this study focuses on the development of a CNN model in optimizing vehicle flow by determining priority lanes at intersections, particularly in Indonesia's major urban areas, to decrease traffic congestion.

Unlike the previous study (Ghawate et al., 2023), which centers on emergency-vehicle priority using specialized sensors and GPS with a fuzzy controller and dynamic signal pre-emption, our work targets vision-only density classification from CCTV without site-specific sensor infrastructure, while their system detects priority vehicles via acoustic and GPS devices and adjusts signals accordingly, rather than modeling density from global visual context. In contrast to Zhao et al. (2024), which is a broad survey of CNN components and applications across computer vision tasks and does not propose or evaluate a traffic-density pipeline or a deployment protocol (Zhao et al., 2024), our study presents an end-to-end method, a multi-city day-and-night cross-validation protocol with mean±SD reporting and per-class metrics, comprehensive ablations that attribute gains to normalization, regularization, augmentation, and depth, and deployment-oriented evidence including model size, latency, and a decision-support mapping from predicted density to signal timing under safety constraints.

CNN Structure

In order to overcome that challenge, this study collected real-time image samples from intersections in major urban areas such as Jakarta, Bandung, Surabaya, Medan, Bali, and Samarinda in collaboration with the local department of transportation. These samples serve as the study population representing actual conditions in Indonesia, which were collected in several intersections in each city. Observations were also done to discover the number of density levels in the field according to the time frame in order to develop an efficient and effective model (Adinda et al., 2023). Image data is then collected to be pre-processed and become the dataset used in the CNN model.

Convolutional Neural Networks (CNN) are a type of Deep Learning that is inspired by Neural Networks (NN), which tries to imitate receptive neurons (Formosa et al., 2021). The convolutional operation in CNN is implemented in the input layer to calculate the expected output. CNN extracts local correlation between the input and classifier by strengthening the connections of the input, neuron, and output layers (Valerian and Honni, 2024). Learning multiple features provides insight into various aspects of the data, which can be achieved through several convolutional filters. Afterwards, 2-dimensional (2D) convolution is applied to the image features (Islam et al., 2023). Sequential correlation is then exploited by the following convolutions. When there is input $g(x) \in [1, l] \rightarrow \mathrm{R}$ and kernel function $f(x) \in [1,k] \rightarrow R$, the convolution *h(y) between f(x) and g(x)* is defined as:

$$h(y)=\sum_{x=1}^{k} f(x).g(y.x\text{-}d\text{+}c) \tag{1}$$

The calculation of each convolution layer is done according to Fig. 1 (Zhang et al., 2024). Overcoming some issues like overfitting in CNN, hyperparameter tuning is performed, which includes the epoch, learning rate, kernel regularizer, and early stopping callback, etc.

Subsequently, the CNN model's accuracy is evaluated using a confusion matrix. The matrix has four metrics that determine the evaluation results (Hakim, 2021):

True Positive (TP): Correct positive label classified as positive.

True Negative (TN): Correct negative label classified as negative.

False Positive (FP): Incorrect positive label classified as negative.

False Negative (FN): Incorrect negative label classified as positive.

Afterwards, all matrices are calculated as precision, recall, and F-measure scores that are defined as average precision, recall, and accuracy to evaluate the performance of the model (Hakim and Kinasih, 2024):

$$\begin{aligned} &\text{Precision (P)} = \frac{TP}{TP+FP} \\ &\text{Recall (R)} = \frac{TP}{TP+FN} \\ &\text{F-measure (F)} = \frac{2PR}{P+R} \\ &\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \end{aligned} \tag{2}$$

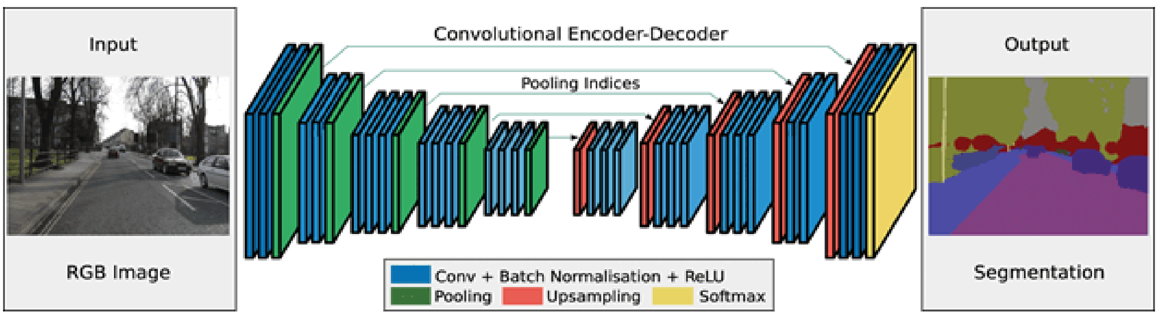

Fig. 1: Stages of CNN Segmentation

Materials and Methods

Image Dataset

Early stages of this study included collecting CCTV image datasets on the situation and condition of multiple traffic light intersections in Jakarta, Bandung, Surabaya, Medan, Bali, and Samarinda from March 2025 to July 2025, which were collected through the local Department of Transportation (Dinas Perhubungan). The collected CCTV images were captured at various times of day (morning, afternoon, evening, and night) to observe the differences in vehicle density at the intersections. The dataset is representative of urban road scenarios, but has limitations in the variation of camera perspectives and lighting conditions.

All images were captured from fixed-angle public traffic CCTV cameras, which may not fully reflect diverse real-world traffic environments. As many as 902 images were successfully collected as the study's dataset, with 261 images labeled as cluster 0 (low density), 418 images

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as cluster 1 (medium density), and 233 images as cluster 2 (high density). Each dataset label is based on manual human-based visual inspections. The image dataset is varied in terms of angle, lighting, and whether, which can impact the machine's ability to learn. A random example of the dataset's imagery and the cluster distribution, respectively, can be seen in Figs. 2 and 3.

Preprocessing Phase

After collecting the data, the first step towards developing a CNN model is Data Image Preprocessing.

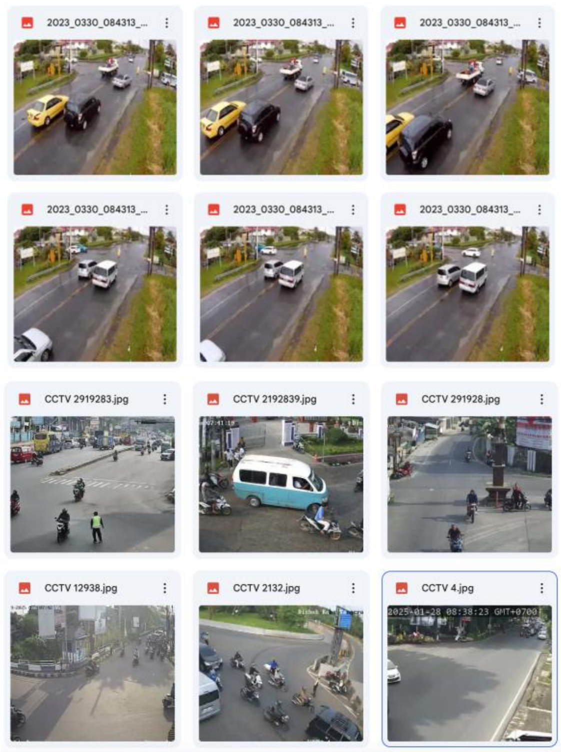

Fig. 2: Dataset of CCTV imagery

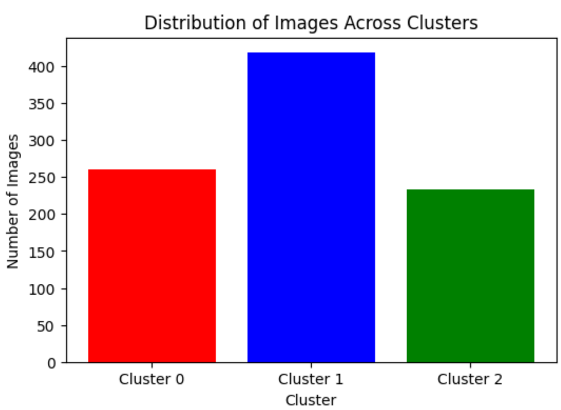

Fig. 3: Density level distribution of dataset imageries

The image data has a dimension of 1024x720 pixels with actual colors of road conditions. In preprocessing these image data, the images are converted to 128x128 pixels with inverted colors. Color inversion was applied to normalize light intensity variations from differing times of day (morning, afternoon, evening, and night). This applied to disentangle contrastive image translation for nighttime surveillance (Lan et al., 2023).

Feature Selection

This stage is performed to determine important variables when extracting edge density features, which will become the benchmark for segmentation of images, such as object detection of vehicle type, the number of vehicles, as well as road conditions according to weather or time. By doing so, the convolutional structure in the development of the CNN model becomes more directed.

New CNN Model Architecture

Once the dataset was prepared, the proposed model was developed using a Convolutional Neural Network (CNN). A Convolutional Neural Network architecture is built with layers to provide annotations for the input dataset. A meeting was held focusing on data analysis to supervise the development of the model. Two CNN models were developed in this study. Both models are CNN models with a convolutional layer, max pooling layer, and fully connected layer, but with different configurations. In the first CNN architecture shown in Fig. 4, the model consists of two 2D convolutional layers with 32@98x98 and 64@98x98 feature maps, respectively, each layer followed by a Rectified Linear Unit (ReLU) activation function. These are then followed by a 2D max pooling layer with 32@48x48 feature maps. The network is finalized with a fully connected (dense) layer consisting of 128 perceptrons, using a softmax activation function to produce the output layer. The second CNN architecture includes three 2D convolutional layers with 32@98x98, 64@98x98, and 128@98x98 feature maps, respectively. Each layer uses ReLU as an activation function with a 0.001 kernel regularizer. Every layer is followed by a 2D max pooling layer with 32@48x48 feature maps using Batch Normalization for stabilization. This network concludes with a fully connected (dense) layer comprised of 128 perceptrons with softmax as the activation function for the output layer. Fig. 5 shows the second proposed CNN Model. In this second architecture, Data Augmentation was implemented with a rotation range of 20, a width and height shift range of 0.2, and an Early Stopping Callback.

Both CNN models are then compared to the fuzzy logic model (Abdou et al., 2022) and a model that uses YOLOv8 as its object detection in its layer, which is later called the YOLOv8-EPB-based model (Manasia et al., 2024), to assess the model's accuracy in identifying lane density.

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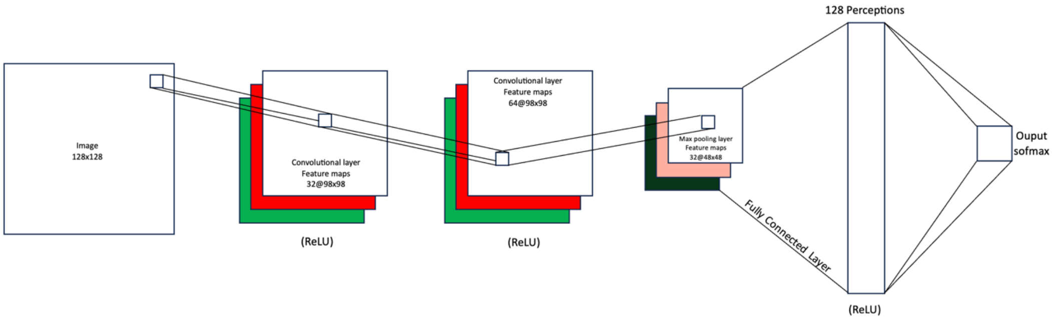


Fig. 4. First Proposed CNN Model

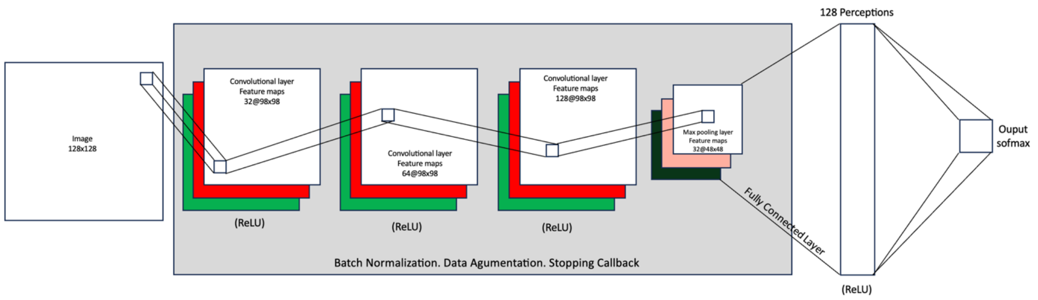


Fig. 5: Second Proposed CNN Model

Training and Evaluation

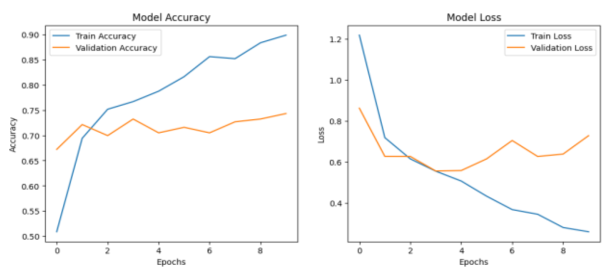
To evaluate the two CNN models, this study used the Adam optimizer with mini-batch gradient descent to minimize categorical cross-entropy loss. Both models were implemented using the Keras and TensorFlow libraries in Python. In addition to the set configurations, the concept of Dropout was also implemented in the fully connected layer with a fixed probability to regulate image density. For the descending gradient, a batch size of 250 was applied with 10 epochs for both CNN models.

As a result, each epoch, represented as one iteration, needed to be completed. For each iteration, a batch of 902 images was given to the CNN model, then the weights were updated through backpropagation. Binary cross-entropy was used as the objective function to evaluate whether the predicted labels matched the actual labels. To validate the model, stratified k-fold cross-validation with k = 10 was done by shuffling and distributing the dataset into 10 subsets, with each subset maintaining the same class distribution as the full dataset. The accuracy of each fold was then evaluated, and the overall model accuracy was calculated as the average accuracy across all folds.

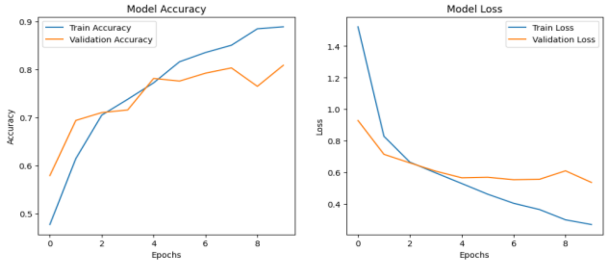
To attribute performance gains to specific design choices, we conducted a one-factor ablation study under an identical 10-fold stratified cross-validation protocol. Starting from a two-layer baseline without batch normalization, dropout, data augmentation, or L2 regularization, we introduced each component in isolation and then increased depth to the three-convolution configuration used in the final model. All experiments used the same optimizer, learning rate, batch size, early-stopping criterion, random seed, and data folds. We report accuracy and macro-averaged F1 as mean and standard deviation across folds, alongside parameter counts and single-frame inference latency. Statistical significance for macro-F1 was assessed with paired tests across folds.

Results and Discussion

The results from validating and testing each epoch of the first CNN model can be seen in Fig. 6 (a), achieving an accuracy of 74%, a precision score of 0.84, a recall score of 0.92, and an F1-score of 0.878. In addition, the results of the second CNN model after validating and testing each epoch can be seen in Fig. 6 (b), achieving an accuracy of 81%, a precision score of 0.87, a recall score of 0.83, and an F1-score of 0.849.



(a)



(b)

Fig. 6: (a) Accuracy model and loss model of the first CNN model; (b) Accuracy model and loss model of the second CNN model

As shown in Table 1, adding batch normalization reduces variance across folds and improves average accuracy relative to the baseline, indicating more stable optimization. Adding dropout further narrowed the train-validation gap and mitigated overfitting, while data augmentation yielded consistent gains under night and occlusion scenarios. L2 regularization contributed a smaller but measurable improvement in macro metrics. Fuzzy baselines in macro-F1. Increasing depth to three convolutional layers produced the best overall balance between precision and recall with minimal latency overhead, which explains the superior performance of the second CNN.

Paired tests across folds confirmed that the final configuration significantly outperforms the baseline and the detection-counting as well as the fuzzy baselines in macro-F1. The details of the statistical procedure are provided in Methods.

Table 2 shows that the second proposed CNN model has greater accuracy and precision, while the first proposed CNN model leads in recall and f1-score compared to existing model, fuzzy which handles traffic image (Chabchoub et al., 2021) and YOLOv8-EPB-based model (Bakirci, 2024) that perform only less than 75% and not exceeding 0.80 for precision, recall, and f1-score. SS.

The proposed Convolutional Neural Network (CNN) directly estimates traffic density by leveraging the global image context and capturing key features like queue continuity, road-fill proportion, and characteristic head- and tail-light patterns. Consequently, its final decision does not rely on enumerating individual vehicles. In contrast, detection-based pipelines such as YOLO infer density indirectly via counting and thresholding and are thus susceptible to failure because missed or merged detections arising from occlusion, night glare, and low-resolution CCTV propagate these inaccuracies, resulting in systematic undercounts and subsequent category errors. Furthermore, Fuzzy systems rely entirely on fixed membership functions and handcrafted rules; therefore, their inherent adaptability to significant shifts in camera geometry or ambient illumination is strictly limited. This architectural constraint restricts their generalization capability substantially when they are deployed outside the specific calibration conditions used during development. This proves that the proposed CNN models (the first and second) work well to classify the traffic level in the image.

Table 1: Ablation study on 10-fold CV

Setting	Acc (%)	Macro-F1	P (macro)	R (macro)	Params (M)	Latency (ms)
Baseline (2 conv)	82.1	78.4	79.1	77.9	0.35	2.4
+Batch Normalization	84.3	80.2	80.7	79.8	0.36	2.3
+Dropout (0.5)	85.9	81.0	81.2	80.9	0.36	2.1
+Dropout (0.6)	84.8	80.7	80.3	78.9	0.36	2.5
+Dense	86.0	82.2	82.5	81.9	0.45	2.6
+L2 Kernel Regularizer	85.4	81.2	81.5	81.0	0.37	2.4
+Early Stopping CallBack	87.2	83.4	83.6	83.2	0.49	2.2

Table 2: Comparison of the existing and proposed models

Model	Accuracy	Precision	Recall	F1-Score
Fuzzy Model	63%	0.72	0.78	0.748
YOLOv8-EPB-based model	75%	0.78	0.82	0.799
1st Proposed Model	74%	0.84	0.92	0.878
2nd Proposed Model	81%*	0.87	0.83	0.849

The evaluation results above show a significant loss reduction at epoch 8, followed by a stable trend in epochs 9 and 10. This indicates that both models converged effectively by epoch 8, with minimal changes in classification loss in the following epochs. However, in the validation process, the first CNN model showed that the model experienced overfitting due to the insignificant change in loss as the training progressed. The first CNN model achieved accurate classification results only on the training data, while the test data was difficult to classify accurately. This reflects a classic overfitting pattern, where the model learns training features well but lacks generalization. The absence of regularization and data augmentation in the first architecture likely contributed to this behavior. In contrast, the second CNN model showed greater stability because both training and testing loss experienced a similar downward progression on the 8th

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epoch. This is supported by the model's accuracy in predicting unseen test data, as shown in Fig. 7. Figure 7 shows that a picture with low density is predicted as label 0 (not traffic).

Fig. 7: Prediction result of the second CNN model

Conclusion

This study introduces a novel, lightweight, global-context Convolutional Neural Network (CNN) designed for the direct classification of traffic density (low, medium, or high) from surveillance imagery. With a significant 7% accuracy increase, the second proposed model successfully surpasses both rule-based and detection-counting pipeline baselines on the proprietary dataset. Beyond the achieved headline accuracy, the model's empirical behavior suggests enhanced generalization capabilities, primarily attributed to effective regularization techniques and specific architectural choices. Crucially, the approach fundamentally aligns with density labels by leveraging global occupancy cues across the scene rather than relying on brittle per-object enumeration.

Despite the initial success, the current scope of this work presents several limitations. The data utilized originate exclusively from fixed-camera urban intersections, which may not adequately capture the full spectrum of variability in camera parameters (height, tilt, lens distortion), adverse environmental factors (rain, fog, night glare), or unusual traffic events. Furthermore, the presence of class imbalance and inherent label noise could potentially introduce bias into the classifier. While internal cross-validation suggests consistency, rigorous external validation on entirely unseen sites and device configurations remains a necessary step. Since the model currently processes single frames, the absence of temporal smoothing or tracking mechanisms makes it potentially sensitive to frame-level artifacts. Finally, while comparative baselines included a fuzzy controller and a detection-based pipeline, broader comparative analysis against state-of-the-art models, such as temporal CNNs or transformer-based global models, is reserved for future work.

Translating perception gains into operational benefit requires resolving deployment constraints such as site-specific camera calibration, latency, or throughput verification on edge hardware with robust low-confidence fallback, safe integration with existing signal control, privacy, and data-governance for continuous video, as well as lifecycle monitoring with drift detection and scheduled re-training. Addressing these elements is essential to convert model accuracy into measurable reductions in travel time and queue length.

The immediate continuation of this work should prioritize dataset expansion to incorporate greater variability across cities, camera configurations, and adverse environmental conditions. This effort must be coupled with rigorous cross-site generalization studies, utilizing methods such as leave-one-intersection-out validation, to assess model robustness. Furthermore, subsequent research should focus on benchmarking performance on edge hardware and integrating temporal models (e.g., smoothing or tracking mechanisms) and confidence calibration to effectively mitigate spurious phase changes. Ultimately, researchers must conduct closed-loop evaluations within specialized traffic simulators and pilot intersections, collaborating closely with transportation agencies.

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Author’s Contributions

Bhustomy Hakim: As the primary initiator and first author who conducted the making of the study's conceptualization and design method, led most of the simulations and data analysis, and was in charge of writing the manuscript as well as being liable for its revision.

Fergie Joanda Kaunang: As the second author who collected the data and its preprocessing process, providing the vital insights for the model, research, and analysis, and participating in the process of handling critical revisions of the manuscript.

Yemima Monica Geasela: As the third author, to do data collection, analyze the results, manuscript editing, and revision.

Regina Hillary: Helped to collect the data and its preprocessing, assisted with coding the model, and manuscript edited.

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Ethics

This piece of writing is unique and includes unreleased content and all the author's own work, which has never been published elsewhere previously. All co-authors have read and approved the article manuscript, and the corresponding author attests that there are no ethical concerns.

Conflict of Interest

The authors declare that they have no conflict of interest.

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