Secure and Safe Traffic Watcher (SSTW): A Smart Application for Future Traffic Monitoring and Response

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CHAPTER I: INTRODUCTION

Traffic accidents represent a significant global concern, accounting for 1.35 million fatalities and an additional 20-50 million non-fatal injuries annually. Given the constant interaction of humans with personal and public vehicles, such tragedies are statistically unavoidable. While the complete eradication of accidents may be an external inevitability, efforts should focus on enhancing accident response mechanisms. Minimizing the time between a traffic accident and the provision of medical treatment is paramount in reducing fatalities. Currently, conventional methods for monitoring and reporting traffic accidents in Indonesia, including manual observation, vehicular sensors, and bystander reports, are inadequate due to their limited coverage and high latency. The implementation of a dedicated monitoring system would address these shortcomings.

The current trend of smart cities in Indonesia are city-wide surveillance systems, CCTVs are strategically placed to cover the widest view possible to detect all vehicle traffic. Applying computer vision to these CCTVs offer a great possibility of detecting and reporting accidents in near real-time. Recently, researchers have shown advances in scene understanding using deep learning models, particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

However, limited research has investigated CCTV-based accident detection using spatio-temporal neural architecture without relying on external object detectors such as YOLO. This methodology typically results in a binary classification problem, where the model discerns between an accident and a non-accident, rather than facilitating continuous scene comprehension and alert generation.

In this paper, we introduce a deep spatio-temporal learning framework for accident detection in surveillance footage, with the objective of generating timely alerts or providing event descriptions. This endeavor aims to contribute to a reproducible benchmark for live CCTV-feed accident detection and underscores the potential of purely video-based deep learning for intelligent traffic monitoring in smart city environments.

CHAPTER II: RELATED WORK

Accident Detection from Video

Early research treated accident detection as an anomaly detection problem, where motion trajectories and handcrafted features were analyzed to spot unusual events [Li et al., 2018; Tian et al., 2019]. These methods, however, struggled with complex traffic scenes and occlusions.

Advancement of Deep Learning in Accident Detection

Researchers began using CNN to capture spatial features in each video frame, like what shapes or objects appear and where. LSTM models are able to capture how those objects in the video move or change over time, capturing temporal features. [Pawar & Attar, 2021; Robles-Serrano et al., 2021]. Several works treated accident detection as anomaly detection [Khan et al., 2022], applying spatio-temporal autoencoders on training datasets of normal driving, and the model flags vehicle accidents as anomalies based on its reconstruction value. These methods achieved strong performance on synthetic or dashcam datasets such as DADA-2000 and A3D, but often failed to generalize to fixed surveillance perspectives.

CCTV / Surveillance-Focused Methods

Recent studies have started leveraging city surveillance datasets with static camera views [Adewopo et al., 2023]. Unlike mobile dashcams, CCTV footage presents stable viewpoints but complex occlusions, varied weather, and multiple motion scales. To handle these challenges, methods have employed ConvLSTM or 3D CNN–based encoders that model scene-level motion rather than relying on object detection.

CHAPTER III: METHODOLOGY

Dataset

The A9 Dataset used in this research is not made publicly available by the creators. The dataset was requested via TUM through providentia. We only utilized one subset of the whole dataset, which is subset 0. This subset of the dataset contains recordings and frames from four camera angles, which is then divided into three parts; where each part contains frames of different weather conditions: **sunny**, **foggy**, and **snowy**. There are 6 categories in total, which are (label ID shown in parentheses): Truck (0), Car (1), Van (2), Trailer (3), Other Vehicles (4), and Pedestrian (5).

Model Setups

Since the main goal of our application, the SSTW, is to detect vehicles thus enabling and providing good tracking performance, we proposed the usage of two models for this task: a model with classical feature extraction in addition to Linear SVC (mirroring the original RCNN architecture), and a YOLOv8n model. We use these two models because we want to compare how the older model and the new model perform. Since the first model does not have a trainable features extraction layer, the feature extraction itself was done offline and only once before training, because the resulting output will not change at any point. These features then became the actual inputs instead of the raw pixels. The raw pixels, however, are still used by YOLOv8n. So, preprocessing and feature extraction are only for the classical model training while resizing is for both the classical model and YOLOv8n.

The models will then be evaluated using different approaches. The classical model focuses a lot more on how the classifier would predict a patch of image to be of substance. This was the reason why the classical model was evaluated in how it would classify a patch of image (in the form of a feature vector) and the classifier as through the detector performance. YOLOv8n is only evaluated as a detector. The metrics are as follows:

- mAP*
- FPS*
- Accuracy**
- Recall**

- Precision**
- F1-Score**
- ROC-AUC**

*detector metric, **classifier metric

Deployment

YOLOv8n is used as the deployed model in the website as it actually performs at a reasonable, possibly real time pace, instead of the two-stage detector like the classical model. YOLOv8n was exported to ONNX, where it was loaded using the Ultralytics' YOLO class. The backend employs a multithreading strategy to ensure that the model's calculations are non-blocking to each other and the server, which may cause huge performance damage if this strategy wasn't employed.

CHAPTER IV: IMPLEMENTATION & RESULTS

EDA and Preprocessing

To 4 before feensure the same size for all inputs, all images were resized to 640x640 while the patches were resized to 128x6ature extraction would be applied to every single image. The preprocessing step involved different methods for different weather conditions. Since vehicles of the same type might have different colors of paint, the colors were omitted by the classical model. This was done by converting all frames to GRAY for the feature extraction itself and all feature extraction methods only received one grayscale channel. All frames were a little grainy, hence a weak median filter was applied before dehazing was done only to foggy frames. The foggy frames had little variations across the axis (which was the primary method to identify them). This characteristic also unfortunately hazed the vehicles, resulting in bad predictions from the model. Dark Channel Prior (DCP) was applied to address this problem. In inference, the feature extraction layer looks for foggy images which are images with variance of laplacian below 50 (the value has been calibrated) before converting to grayscale (or else the layer will not know the variance of laplacian. CLAHE was applied to finalize the preprocessing because some images showed signs of unbalanced saturation.

All preprocessed images' features were then extracted using two methods: HOG and LTP. HOG was used because most variants were in the gradients, such as in how the values differ compared to their surroundings. However, HOG produced dynamic-sized vectors which were not ideal for classical models. This is why PCA was used to scale down the HOG length to a fixed-size. The PCA was trained on all features, then was run on 20 images to get the median of those images, where the coefficient computed up to around 95%; roughly about 839. Uniformity was applied to LTP to fix the vector length to 119, making it static. These features were then concatenated to form a vector of length 958 for the input.

Model Training

The Linear SVC training was done on a jupyter notebook with the default parameter, which is **C = 1.0**. Linear SVC only has one parameter, C, the penalty parameter which controls the trade-offs between model complexity and performance. In this case, 1.0 was good enough as each sample has a lot of variations, but ensures that the model is not hallucinating or underfitted. A linear kernel was used to mimic the original RCNN architecture and to also handle the typical pattern of classical feature extraction method output. The Linear SVC itself was trained using the method OvO and OvR to see which training and inference method would lead to better performance. The classifier was then exported to ONNX format to then be loaded up by the classical model class which also has the feature extraction layer for inference.

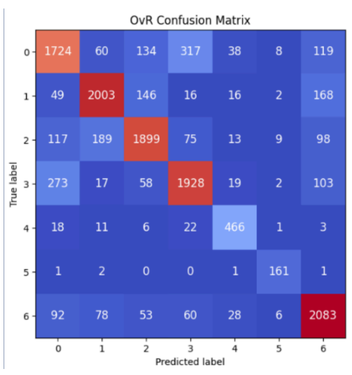
YOLOv8n was trained using its default parameters without modifications on the unprocessed resized to 640x640 images. The training was done across 100 epochs with the batch size of 32 and a patience of 10. The resulting parameters were then exported to ONNX format in two different forms: an fp32 normal ONNX model and a 16-bit quantized format, both of which had been simplified through Ultralytics' method, reducing redundant calculations.

Deployment

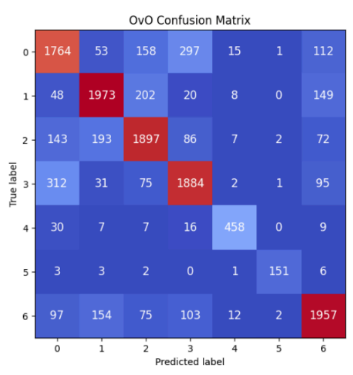
The deployment is done using two different tech stacks, which mostly consist of the backend and the frontend. The backend uses Flask to serve the routes while utilizing threads and ONNX runtime to run the actual ONNX models. This mimics how the model would run on the edge side before going through fog then cloud (dashboard). The frontend utilizes Next.js for its versatility when developing either static or dynamic pages. Since SSTW contains both static pages (landing page, articles, etc) and dynamic pages (dashboard, alerts, etc), Next.js rendering methods; such as SSG, SSR, and Client-Side Rendering, helps a lot in the frontend and potential future deployment.

Results

Classical Classifier

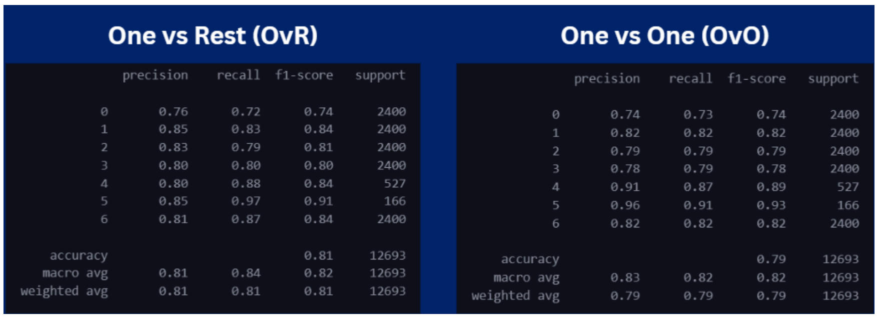

OvR Confusion Matrix

True label \ Predicted label	0	1	2	3	4	5	6
0	1724	60	134	317	38	8	119
1	49	2003	146	16	16	2	168
2	117	189	1899	75	13	9	98
3	273	17	58	1928	19	2	103
4	18	11	6	22	466	1	3
5	1	2	0	0	1	161	1
6	92	78	53	60	28	6	2083


OvO Confusion Matrix

True label \ Predicted label	0	1	2	3	4	5	6
0	1764	53	158	297	15	1	112
1	48	1973	202	20	8	0	149
2	143	193	1897	86	7	2	72
3	312	31	75	1884	2	1	95
4	30	7	7	16	458	0	9
5	3	3	2	0	1	151	6
6	97	154	75	103	12	2	1957

Fig. 1: Classical classifier confusion matrix.



One vs Rest (OvR)

```
              precision    recall  f1-score   support

           0       0.76      0.72      0.74      2400
           1       0.85      0.83      0.84      2400
           2       0.83      0.79      0.81      2400
           3       0.80      0.80      0.80      2400
           4       0.80      0.88      0.84       527
           5       0.85      0.97      0.91       166
           6       0.81      0.87      0.84      2400

    accuracy                           0.81     12693
   macro avg       0.81      0.84      0.82     12693
weighted avg       0.81      0.81      0.81     12693
```

One vs One (OvO)

```
              precision    recall  f1-score   support

           0       0.74      0.73      0.74      2400
           1       0.82      0.82      0.82      2400
           2       0.79      0.79      0.79      2400
           3       0.78      0.79      0.78      2400
           4       0.91      0.87      0.89       527
           5       0.96      0.91      0.93       166
           6       0.82      0.82      0.82      2400

    accuracy                           0.79     12693
   macro avg       0.83      0.82      0.82     12693
weighted avg       0.79      0.79      0.79     12693
```

Fig. 2: Classical classifier classification report.

The classical classifier performed well during training. There were two training setups for the classifier which involved the training method: One vs One and One vs Rest. The One vs One training method created 21 classifiers, where each classifier is tuned to compare one class with the other, and the highest confidence will be picked as the label. One vs Rest trained only 7 classifiers which are focused on determining one label against another label on one model, instead of one by one. On paper, the one vs one training method has a better chance to classify the labels, but the results show the opposite performance.

The one vs one training method had better generalization, especially on rare classes, which are class 4 and 5 (other vehicles and pedestrians). In comparison, the one vs rest training method performed better in every other class and had a better overall macro performance which potentially would do better to the overall detector performance.

Classical Detector

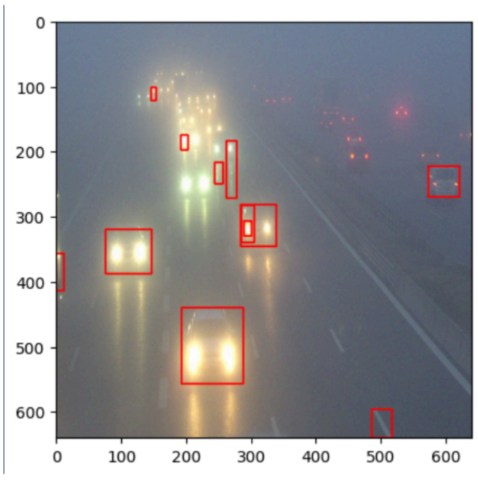


Fig. 3: Classical detector sample prediction.

Metrics	Value
mAP	0.77%
mAP50	1.6%
mAP75	0.6%

Fig. 4: Classical detector mAP over 30 frames.

The classical detector had really low recall. This most likely was caused by the classifier not being able to identify small and occluded vehicles. Meanwhile, the classical detector mAP is also low with only 0.77% overall. This indicated that there was a discrepancy between the classifier performance and the detector pipeline. This was likely because the feature extraction layer was not robust to variance even with HOG and LTP combined.

YOLOv8-n

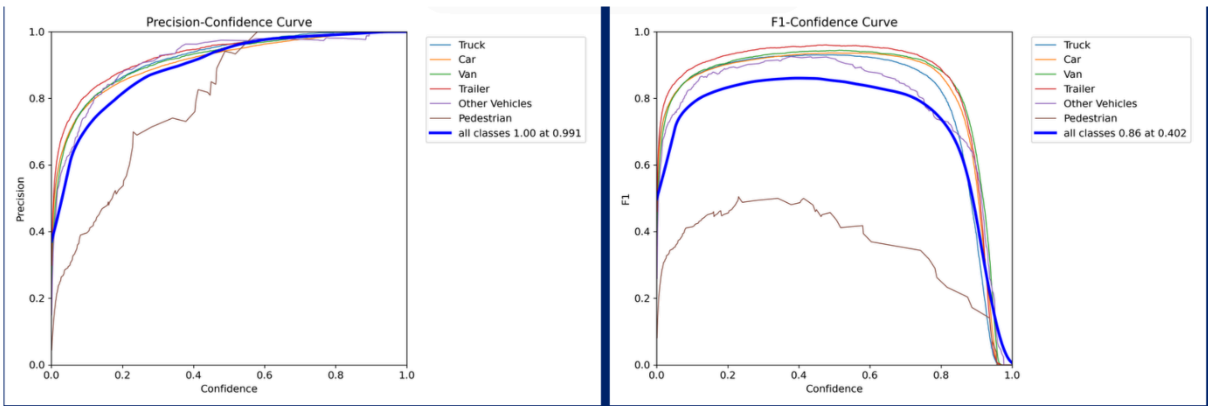


Fig. 5: Precision-confidence and F1-confidence curve

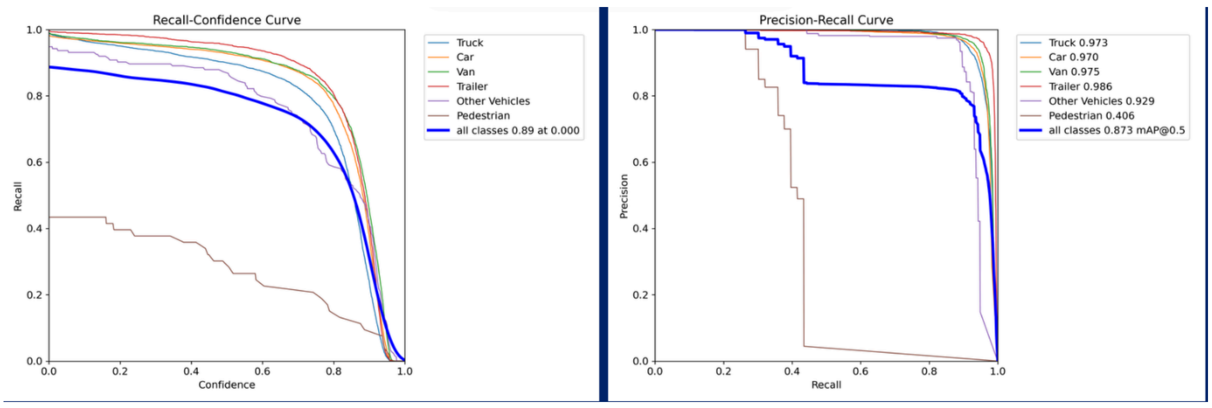


Fig. 6: Recall-confidence and precision-recall curve

All three metrics: precision, recall, and F1; are dropped on high-confidence boxes. This is because YOLO is more selective with its detections. This caused low recall by the model when predicting high confidence boxes. This also caused a drop on the precision when predicting these high confidence boxes.

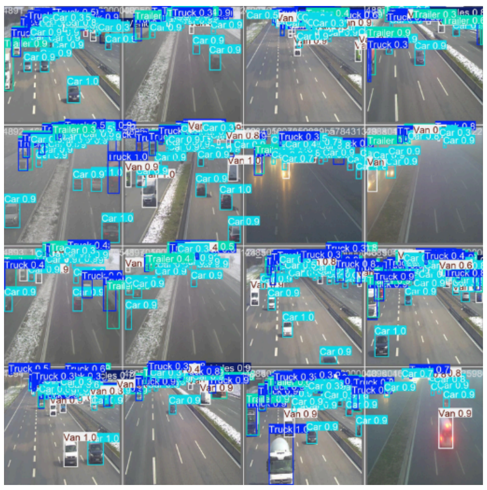


Fig. 7: Sample predictions

YOLO created tight bounding boxes. This is a typical behaviour as YOLO employed a box refinement process, not only creating raw bounding boxes. In all predictions, it could also be seen that YOLO could even predict occluded and small objects.

Metrics	Value (FP16)	Value (FP32)
mAP	76.15%	76.09%
mAP50	83.68%	83.68%
mAP75	81.09%	81.16%

Fig. 8: YOLO mAP over 30 frames.

Comparing the compression, YOLO performed similarly before and after quantization. The original FP32 model size was around 12 MB before quantization and only 6 MB remained after quantization. Quantization proved to be good since the performance did not drop.

Model	Frame Per Second	Latency (s)
Classical Model	0.005	200
YOLOv8n FP16	19.94	0.05

YOLO v8n FP32	27.77	0.036

Fig. 9: FPS and latency of each model.

The classical model is a two-stage detector, hence the high latency and < 1 FPS. This immediately eliminated the viability of it being in a real-time traffic watcher system. YOLOv8n models have lower latency as they are one-stage detectors. YOLOv8n FP16 once again delivered better performance compared to the original FP32 version. It inferred one model with only 71.8% of time the original FP32 version took.

CHAPTER V: DISCUSSION & LIMITATIONS

This study compared a classical two-stage detection pipeline with a modern deep learning–based one-stage detector for traffic object detection under challenging environmental conditions. The classical approach combined handcrafted features (HOG and LTP) with a Linear SVC classifier, while YOLOv8n represented the deep learning baseline.

The classical classifier demonstrated strong performance during isolated classification, particularly when trained using the One-vs-One (OvO) strategy, which showed better generalization on rare classes such as pedestrians and other vehicles. Meanwhile, the One-vs-Rest (OvR) strategy achieved better overall macro performance, suggesting that OvR is more effective when class balance and overall detector consistency are prioritized. This indicates that the choice of multi-class strategy significantly affects performance depending on class distribution and target use cases.

The test results for the classical models conclude that the combination of classical feature extraction and classifier is not ideal for a real-time traffic monitoring system, as it is computationally slow and not robust when implemented in the final detection pipeline. From the test results, it shows extremely low recall and mAP, thus shown being unable to handle large variances in scale, occlusion and environmental noise. Small and partially occluded vehicles were particularly difficult for the classical detector to identify, which significantly impacted recall.

On the other hand, YOLOv8n achieved a high performance and tight bounding boxes in the final detection pipeline, which shows its capability of detecting small and occluded objects. YOLOv8n also appeared to be stable in the training process with no sharp fluctuations, overshooting, or any other symptoms of bad training behaviours. We can credit this advantage to the internal feature hierarchy and learning process that allows the model to learn contextual and spatial relationships that classical feature extraction is unable to capture.

Moreover, the difference in latency in both models are drastically different. The classical detector’s two-stage architecture was inefficient and computationally expensive, only achieving a maximum of 1 FPS. While YOLOv8n was a one-stage detector that was quantized to its FP16 version (50% of its original size), achieved much faster inference, making it ideal for real-time edge-deployment purposes for monitoring systems in CCTVs.

The experiment concludes that modern deep learning based detectors are far more effective than classical methods for real-time, end-to-end traffic object detection with low visibility, intense environmental noise and changing weather conditions.

The limitations of our study are several. Firstly, the classical feature extraction relied on grayscaling images and handcrafted features, which limits representational capacity. Classes that may have similar shapes but different visual contexts, like van and SUV, may be misclassified due to the removal of potentially useful discriminative information.

Second, Laplacian threshold for fog detection and preprocessing may not generalize well to different lighting conditions, noise and camera qualities than the ones seen in the dataset. This can increase errors in fog classification, which impacts preprocessing and downstream detection performance. Third, PCA-based dimensionality reduction may also discard discriminative features that are key for rare classes. Lastly, we used the default hyperparameters of YOLOv8n without task-specific tuning.

CHAPTER VI: CONCLUSION & FUTURE WORK

All in all, the Secure and Safe Traffic Watcher (SSTW) performs its job well although it may struggle with noisy images and defective images (fog, for example), being able to detect congestion and traffic decently well as well as give an analysis based on its results and statistics, dependant on the traffic showcased within the image/video.

This technology may prove to be useful in the future, especially in regards to how the usage of deep neural networks as classical feature extractions may fail (as seen within our case, hence as a learning point for future works), as well as additionally finding the use of DeepSORT to track vehicles instead, which may prove much more efficient and reasonable in comparison to our current methods. In this case, future works may be inspired by the technology employed within the Secure and Safe Traffic Watcher, hence the implementations and considerations put forth.

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APPENDIX

Team Contribution Statements:

Name	**Contributions**
Ian Mulya Chiuandi - 2702218891	PPT Presentation (Original + Refactoring), Final Report (Chapter 1-2, 6), Web App Frontend (Jinja Templating via index.html), Web App Backend (Setup Flask app.py, Input Image/Video, Send Media to Server), Model (FasterRCNN Attempt), Demo Video Recording
Stanley Jonathan Wahjudi - 2702210232	Data handling, preprocessing, model training, frontend and backend refactoring (Enhance pages and adapt websocket), initial demo video recording + editing, demo video editing, and documentation, ppt creation, final report (Chapter 3-4).
Jonathan - 2702307972	Ideation, researching, final report, ppt refactoring, demo video recording, backend frontend prototyping, final report (Chapter 5)