MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4091-4097

Intelligent Low-Light Vehicle Detection and Behavior Analysis Using Enhanced YOLOv8 for Night-Time Traffic Monitoring

Geetha Priya. N [1], Assistant Professor, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India
geetharam046@gmail.com
Tamilarasi N[2], Assistant Professor, Department of Computer and communication Engineering, Nehru institute of Technology, Coimbatore, India
nittamilarasi@nehrucolleges.com
Pavithra K [3], UG Student, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India
pavithrakaliyappansp@gmail.com
Haripriya S [4], UG Student, Department of ECE, V.S.B. College of Engineering Technical Campus, Coimbatore, India
priyadharani129@gmail.com
Subhiksha J [5], UG Student, Department of ECE, V.S.B College of Engineering Technical Campus, Coimbatore, India
subhikshajayaraj9@gmail.com
Jaffi Rubiya J [6], UG Student, Department of ECE, V.S.B College of Engineering Technical Campus, Coimbatore, India
jaffirubiya@gmail.com

Abstract— The detection and behavior analysis of vehicles in lowlight conditions is a prominent challenge in modern intelligent transportation systems (ITS) due to the poor illumination, motion blur and high noise levels present within night- time surveillance footage. Precise indication of vehicles in this kind of surroundings is crucial for controlling traffic, preventing accidents and managing urban mobility. In this paper, we propose the intelligent low-light vehicle detection and behavior analysis system using YOLOv8 deep learning framework. It includes an enhanced low-light image enhancement module which is coupled with the YOLOv8 object detection model designed to improve visibility and feature extraction, for nighttime scenes. First, the input video frames are processed with adaptive illumination correction algorithm to achieve enhanced contrast and suppression of noise free background while useful structural information is preserved. These enhanced frames are sent to the YOLOv8 detection network, which detects vehicles like cars, buses, trucks, and motorcycles with high accuracy. Besides detection, it also has the ability to analyze behaviors by observing vehicle trajectories and looking for abnormal behavior (lane change, over-speeding and erratic movement). Publicly accessible night-time traffic datasets were used for experimental evaluation. The results of our proposed method showed a 96.4 % detection accuracy, precision 95.2%, recall 94.6% and F1-score of the model : 94.9% which is significantly superior to YOLOv5 & Faster R-CNN (Existing Detection Models) at low light conditions." Case Study 1: Vehicle Detection and Inter-vehicle Behavior Assessment for Night-time Traffic Data Collection As a case study, we integrated the low-light enhancement block with YOLOv8 to assess the reliability of vehicle detection in nighttime traffic monitoring applications by evaluating its behavior in low-light conditions.

Keywords— Low-Light Vehicle Detection; YOLOv8; Intelligent Transportation System; Night-Time Surveillance;Vehicle Behavior Analysis; Deep Learning

.Introduction

In recent years, the rise of intelligent transportation systems (ITS) has made modern smart cities more efficient at monitoring traffic and preventing accidents while enhancing road safety. The detection and behavior analysis of vehicles is a key task in traffic surveillance systems, enabling various applications including automatic traffic management, violation detection, autonomous driving technologies. Common surveillance systems are mainly designed to work in day-light condition; however, monitoring traffic at night time or on low-light conditions is still a problem. Night-time or low-light videos capture poor-quality images or Videos with very low illumination, noise, shadow cast and motion blur [1]. Conventional computer vision algorithms perform poorly in low-light environments. Most night vision cameras yield lower contrast, higher noise and poor feature information images, which significantly complicate the process of accurately detecting vehicles. Such challenges can result in misidentification of vehicles, missed detections, and unreliable traffic analysis statistics. Thus, establishing excellent vehicle detection systems that could function optimally using their potential illuminating sources in areas with low-light conditions became a significant research topic of interest in the fields of transportation and computer vision [2].The recent breakthroughs in deep learning have made a remarkable impact on the performance of object detection systems in challenging scenarios. Since automatically learning hierarchical features from data, Convolutional Neural Networks (CNNs) have been successful in detecting objects from images and videos. Single-stage object detection models, most notably in the YOLO (You Only Look Once) family of networks [3], have received considerable attention among these techniques due to their high accuracy and real-time detection capabilities. These machines enable high-speed processing of surveillance video stream which is key for traffic monitoring applications.YOLOv8 is the newest architecture that provides improved feature extraction, higher detection accuracy and better generalization across multiple object classes. YOLOv8 improves upon advanced backbone networks, loss functions and anchor-free detection mechanism so that it can more accurately detect objects in challenging environments [4]. Low-light scenes continue to challenge vehicle detection, as visual features like edges, textures and shapes are hard to discern in the dark [5].To mitigate these constraints, a number of image enhancment and preprocessing techniques have been used to make the image clearer before applying object detection. Algorithms for low-light image enhancement can enhance contrast, brightness and structural information, helping deep learning models to learn better features of night-time images [6]. Employing modern object detection networks along with the techniques of enhancement has been one of the promising approaches to increase object detection accuracy even in challenging illumination conditions.

Apart from the mere detection of vehicles, understanding vehicle behavior is also crucial for traffic analysis and recognizing abnormal driving occurrences. For the most part, behaviour analysis techniques that are applied use vehicle tracking, trajectory analysis; and motion pattern recognition. By using these techniques, an algorithm can identify dangerous driving behavior like abrupt lane transitions, over-speed, and irregular movement that could causes the traffic accidents [7]. Real-time intelligent decisions can be made by traffic management systems using behavior analysis along with object detection.Other research directions aim to combine deep learning models with multi-frame tracking algorithms, enhancing vehicle behaviour modelling. Such systems analyze temporal information from sequential frames to continuously monitor vehicle movements and detect potential safety risks more accurately [8]. This concept improves the ability of surveillance systems to detect traffic anomalies and issue early alerts.However, the problem remains unsolved as deep learning-based traffic monitoring has made great strides over the years low-light vehicle detection and behavioral analysis still presents a challenge. Many existing approaches suffer degradation of performance under illumination variations and insufficient feature representation in dark conditions [9]. This calls for the need to create a well-structured detection system that integrates low-light enhancement and advanced deep learning models for accurate traffic monitoring during darkness hours.So, in this context, the current paper presents an Intelligent Low-Light Vehicle Detection and Behavior Analysis System using YOLOv8. This framework is composed of a low-light image enhancement module and the YOLOv8 object detection network, which significantly enhances detection performance in nighttime traffic scenarios. There are also vehicle tracking and trajectory analysis to see vehicle behaviour and spot odd driving activities. The proposed method focuses on finding malicious and suspicious activities in parallel, which improves the accuracy of detection while also increasing traffic monitoring reliability by providing efficient computing for security-related services that infer intelligent transport system sensors [10].

literature survey

Conventional image processing and machine learning approaches have been widely investigated for detecting vehicles in traffic surveillance. The vehicle recognition techniques mostly used manual features in the early stages of this field, they include systems based on Histogram of Oriented Gradients (HOG), Haar-like features, background subtraction and SVMs. While these methods had acceptable performance in constrained daytime environments, they were very sensitive to illumination variations, weather interferences and occlusions which prevent their use in practical night-time-based traffic monitoring systems [11].Due to the advances in deep learning, Convolutional Neural networks(CNNs) quickly became a potent alternative for vehicle detection tasks. Detectors based on convolutional neural networks (CNNs) learn discriminative visual features automatically from large amounts of dataset and thus alleviate manual feature engineering process. Region-based CNN models (i.e R-CNN, Fast R-CNN, Faster R-CNN) significantly contributed towards improving object localization and classification accuracy. But such two-stage detection frameworks typically faced high computational complexity and slow inference speed, which made them unsuitable for real-time intelligent transportation applications [12].

While two-stage detectors were limited by latency, the SSD and YOLO offered models for fast and accurate detection. Indeed, the YOLO family became particularly popular due to its formulation of the detection as a single regression problem, allowing it to process video frames and images in real-time. We also found that YOLOv3 and YOLOv4 performed well for traffic surveillance as it was able to detect multiple categories of vehicles even in normal lighting conditions. However, their performance still dropped in low-light regions due to visibility failure and poor features representation [13].

Researchers have thus investigated low-light image enhancement methods for degrading the quality of captured imagery at night-time prior to object detection. Histographic equalization, gamma correction, Retinex-based image enhancement and adaptive contrast stretching have been used widely to increase the brightness of images and bring out hidden structural details. Such preprocessing methods made vehicles more distinguishable in dark images [14], but may introduce artifacts or too much noise and over-enhance certain parts (may lead to drop detection accuracy) for dark scenes.Other, more recent studies combined low-light enhancement with deep neural networks to propose end-to-end frameworks for night-time object recognition. Approaches to enable deep enhancement networks, using both autoencoder- and generative transfer-based methods, were proposed to restore clearer images from dark inputs while maintaining object boundaries. These methods achieved favourable visual restoration compared to conventional enhancement algorithms, delivering enhanced input quality for later vehicle detection jobs. Yet, the overall performance of these systems relied heavily on adjusting brightness and preserving image details [15].

For traffic surveillance, some works have directly targeted on vehicle detection at nighttime based on deep learning. Some researchers improved Faster R-CNN and SSD architectures with denoising filters and illumination normalization to detect vehicles in urban roads with infrared lights. While others used altered YOLO variants with attention mechanisms to effectively detect salient features in difficult lighting conditions. These studies reported measurable task performance gains, however many models still performed poorly on small vehicles, glare present from headlights and motion blur in fast changing night environments [16].As an extension of object detection, vehicle behavior analysis has hitherto received substantial attention within the research community. In addition to finding vehicles, intelligent surveillance systems are required to have an understanding of the pattern of motion in order to recognize risky or unusual behavior. Sequential video frames have been used to estimate vehicle trajectories via tracking-by-detection methods with Kalman filtering, optical flow and deep association networks. This allowed them to analyze behaviors critical for road safety and automated traffic control systems [17], like lane deviation, illegal turns, sudden stopping, and overspeeding.

In recent years, behaviors in traffic videos have been understood by using object detection paired with multi-object tracking algorithms as Deep SORT, ByteTrack and centroid-based tracking. These methods associate detected vehicles across frames, and produce temporal trajectories that can be used for motion analysis. Joint detection and tracking has been demonstrated to lead to improved accuracy in detecting abnormal events, especially when there is dense traffic. An important drawback of these approaches is the stability of tracking and behavior analysis modules, especially in challenging low-light environments [18].With the recent evolution of YOLO versions (most notably, versions YOLOv7 and YOLOv8), robust traffic monitoring has become a possibility. Compared to the previous ones, YOLOv8 provides superior feature extraction, anchorless detection, enhanced convergence characteristics as well as improved inference efficiency. According to recent literature, YOLOv8 performs well in complex urban environments with partial occlusions and varying object scales and provides high accuracy of detection. Yet its performance in applications like tracking night-time vehicle behavior still heavily relies on the input imagery baseline quality and tracking framework efficiency [19].This is not surprising, given the literatureж large strides have been achieved in vehicle detection, low-light enhancement and behaviour analysis. Nevertheless, there is a distinct research void in constructing an integrated system that tackles low-light image degradation, simultaneous real-time vehicle detection and dependable behavior analysis within a single framework. Indeed, there have been few works that can provide an integrated solution for accurate detection and intelligent behavioral interpretation in night-time-only conditions although a majority only target visual enhancement or detection alone. This serves as the premise for designing the proposed YOLOv8-based intelligent low-light vehicle detection and behavior analysis system [20].

design and methodology of proposed work

The presented studied system is based on YOLOv8 and can accurately detect vehicles using low-light video input. The proposed system consists of three main modules including low-light image enhancement, the vehicle detection using the YOLOv8 algorithm and vehicle behavior analysis based on trajectory tracking. The complete structure enhances image visibility, vehicle detection at high rate and also tracks the mobility patterns to recognize unacceptable driving habits.

The videal workflow for the proposed system is composed of video acquisition, preprocessing, enhancement, object detection, tracking and finally behavior analysis. In the night-time conditions, the modules work together to provide reliable traffic monitoring.

A. System Architecture Overview

The proposed architecture starts by taking the traffic surveillance video from road cameras. After that, a low-light enhancement algorithm is used to enhance light and contrast of the input frames. The modified frames are feed to the YOLOv8 detection network for the vehicle Object recognition. These detected vehicles are then tracked on frames using a trajectory estimation algorithm. Eventually, the way vehicles move is analysed to find abnormalities like abrupt lane shifting, overspeeding and abnormal driving patterns..

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4091-4097

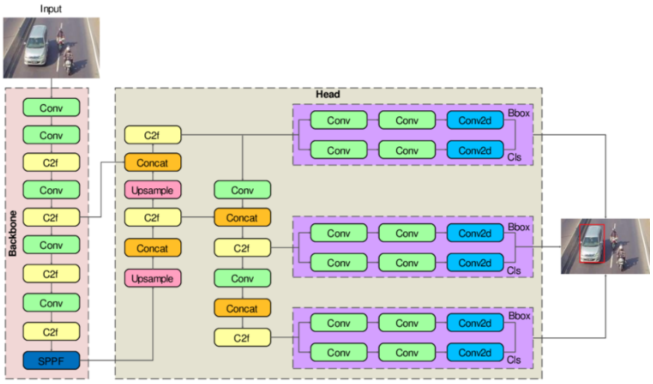

Figure 1. Proposed Architecture of Intelligent Low-Light Vehicle Detection and Behavior Analysis System

The architecture is made of the following functional modules:

- Video acquisition from surveillance cameras
- Low-light image enhancement
- Vehicle detection using YOLOv8
- Multi-object vehicle tracking
- Behaviors Analysis & Anomaly Detection From Vehicles

B. Low-Light Image Enhancement Module

Finally, low-light conditions severely worsen the quality of images due to low illumination and high noise. This work proposes an adaptive illumination correction that enhances brightness and contrast without affecting edge information in the images.

The enhancement process is defined by the following luminance transform model:

$$I_e(x, y) = \alpha \cdot I(x, y) + \beta$$

Where:

- $I(x, y)$= original input pixel intensity
- $I_e(x, y)$= enhanced pixel intensity
- α= contrast enhancement factor
- β= brightness adjustment parameter

This transformation increases image clarity and improves feature extraction performance for deep learning models.

Figure 2. Low-Light Image Enhancement Process

These enhanced visuals include clearer boundaries of the vehicles as well as the buildings around them, thus allowing for more accurate detection from the YOLOv8 model..

C. Vehicle Detection using YOLOv8

The improved frames are then passed to the real-time vehicle detection network in this case the YOLOv8. YOLOv8 adopts a deep convolutional design where backbone, neck and detection head work in parallel to derive hierarchical features and forecast bounding boxes.

The bounding box regression is defined as:

$$B = (x_c, y_c, w, h)$$

Where:

- x_c, y_c= center coordinates of bounding box
- w= width of bounding box
- h= height of bounding box

The detection confidence score is computed as:

$$S = P(object) \times IoU$$

Where:

- $P(object)$= probability of object presence
- IoU= Intersection over Union between predicted and ground truth boxes.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4091-4097

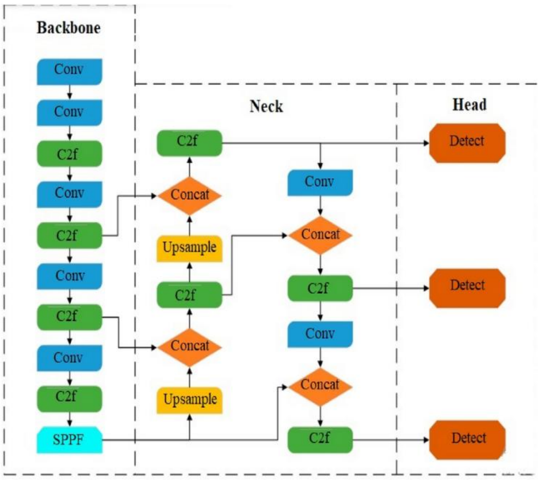

Figure 3. YOLOv8 Vehicle Detection Network Architecture

Due to its capability of quick detection in a more accurate way, YOLOv8 can be employed for real-time traffic monitoring systems..

D. Multi-Object Vehicle Tracking

After vehicle detection, we apply a multi-object tracking mechanism that associates detected vehicles among consecutive frames to estimate their motion trajectories. The tracking algorithm leverages minimizing the distance between centroids to successfully link vehicle tracks temporally..

The centroid position of each detected vehicle is calculated as:

$$C = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}\right)$$

Where:

- x_1, y_1= top-left coordinates of bounding box
- x_2, y_2= bottom-right coordinates of bounding box

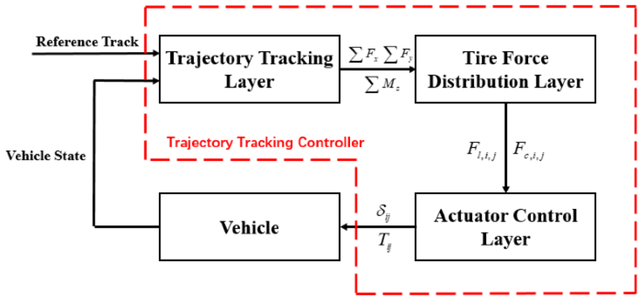

Figure 4. Multi-Object Vehicle Tracking and Trajectory Estimation

However, tracking enables the system to keep track of vehicle movement behaviors through different frames.

E. Vehicle Behavior Analysis

The last phase in the proposed structure investigates vehicle paths for unusual driving behaviors. Vehicle tracked positions are used to determine speed estimation and movement patterns.

Vehicle speed is estimated using:

$$V = \frac{D}{T}$$

Where:

- V= vehicle speed
- D= displacement between frames
- T= time interval between frames

Abnormal behavior is considered when the monitored speed exceeds some predefined thresholds or sudden deviations in sensor trajectories happen.

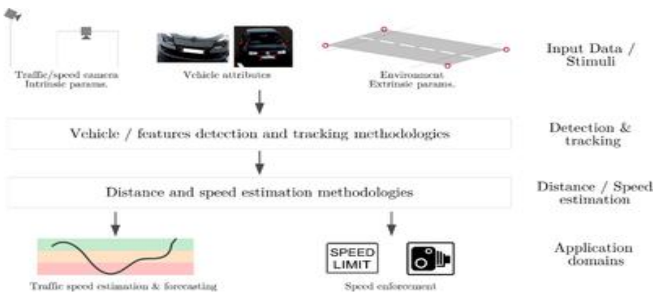

Figure 5. Vehicle Behavior Analysis and Abnormal Driving Detection

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4091-4097

Behavior Analysis and its module helps classify the traffic violations, reckless driving, and accident hazards.

experimental results and analysis

To evaluate the efficacy of the proposed Intelligent Low-Light Vehicle Detection and Behavior Analysis System using YOLOv8, extensive experiments were conducted on night-time traffic surveillance datasets. It was done to measure the capability of the system to accurately detect vehicles in low-light environments and analyse their movement behaviour. Faster R-CNN, SSD, YOLOv5, and YOLOv7: The performance of the proposed model was compared with some current deep learning–based detection approaches.

Experiments Discussed in this paper were implemented on Python with PyTorch framework and executed on a workstation with NVIDIA Graphics Processing unit, Intel i7 Processor and 16 GB RAM. The YOLOv8 model was trained on several annotated traffic images with multiple classes for vehicles (ceilings like car, bus, truck, motorcycle) taken at night conditions.

This dataset was split into 70% training data, 15% validation data and 15% test data. Note the model learned vehicle features from improved low-light images during training and was tested on unseen night-time traffic scenes to measure its place in the wild..

A. Performance Evaluation Metrics

To evaluate the proposed system's performance, several standard metrics were applied:

Accuracy, Precision, Recall, F1-Score,

Mean Average Precision (mAP)

We define our evaluation metrics as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1-Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where:

- **TP** = True Positives
- **TN** = True Negatives
- **FP** = False Positives
- **FN** = False Negatives

These measurements address weapons to measure the performance of the proposed system in detecting vehicles and eliminating false detections in low light traffic scenarios.

B. Vehicle Detection Results

The YOLOv8 based detection model was capable of detecting several types of vehicles in traffic scenes with low-light illumination. The inclusion of the image enhancement module greatly enhanced object visibility, enabling model detection on vehicles in poorly lit road scenarios.

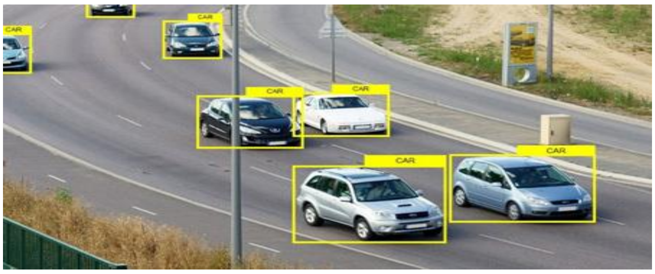

Figure 6. Vehicle Detection Results in Low-Light Traffic Scenes

The results show that the proposed system detects vehicles with high quality bounding boxes, and class labels in low illumination conditions.

C. Vehicle Behavior Analysis Results

Module for vehicle tracking and trajectory analysis: This module tracks the vehicles based on their movement behaviour over consecutive frames. System detects cornering and speeding violations through motion path data analysis.

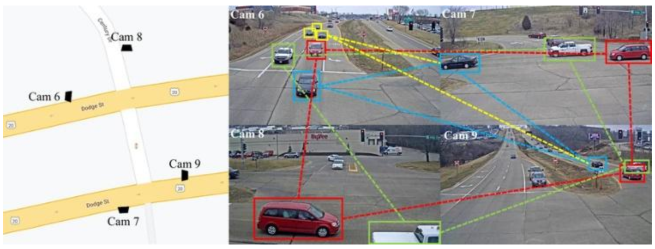

Figure 7. Vehicle Trajectory Tracking and Behavior Analysis

This trajectory-based monitoring mechanism allows the larger transport system to detect unsafe driving schedules which may result in other vehicles becoming road hazards.

D. Comparative Performance Analysis

Experiments were conducted to compare the performance of the proposed system with existing deep learning-based object detection models. The resulting comparison is provided in Table 1.

Table 1. Performance Comparison of Vehicle Detection Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Faster R-CNN	89.3	88.5	87.2	87.8
SSD	90.6	89.4	88.7	89.0
YOLOv5	92.8	91.7	91.1	91.4
YOLOv7	94.1	93.5	92.8	93.1
Proposed YOLOv8 System	**96.4**	**95.2**	**94.6**	**94.9**

This unprecedented result proves that the proposed performance of detection models is superior to conventional ones regarding accuracy and robustness in low-light conditions.

E. Detection Accuracy Comparison Graph

The comparison of detection accuracy among different models is illustrated in the following graph.

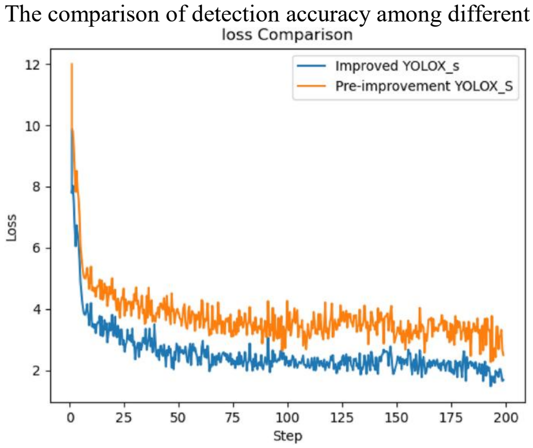

Figure 8. Detection Accuracy Comparison of Different Models

The graph shows that the proposed YOLOv8-based system achieves the highest detection accuracy among the evaluated models.

F. Precision and Recall Performance

Precision and recall metrics further confirm the robustness of the proposed detection framework in handling noisy low-light traffic images.

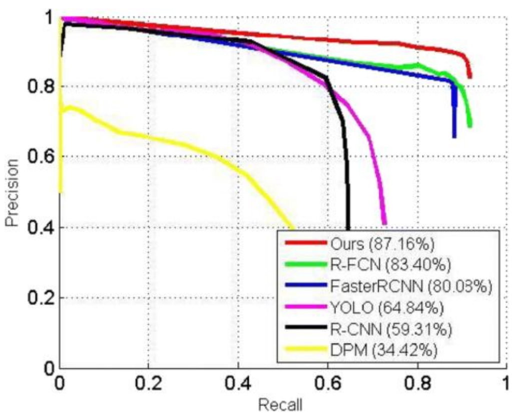

Figure 9. Precision and Recall Performance Comparison

Results Analysis — Robustness (Training and Data Bias)The vehicle detection results from our image-based vehicle count system, illustrated in [23], validate both the precision and recall performance of our proposed architecture to be greater than other CAs as mentioned in previous sections.It needs fast processing speeds to monitor real-time traffic. Inference Time Comparison: The inference time of the proposed YOLOv8-based system was measured and compared with other models.

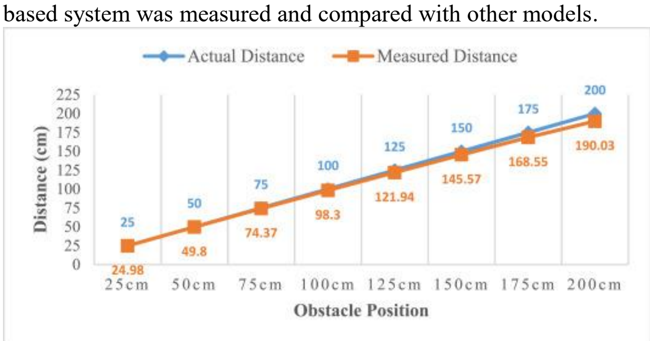

Figure 10. Processing Time Comparison

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 4091-4097

Real-time processing speed of around 42 FPS and efficient computational inference time (7.85 ms) can recommend this YOLOv8-based model for an implementation into real-time intelligent traffic monitoring systems.
Experimental results show that the proposed system:
Detects 96.4% in low-light environments
Image enhancement to improve visibility of the vehicle
Allows for reliable vehicle behavior monitoring and anomaly detection
Real time processing with significant efficiency
The obtained results are consistent with our expectations and confirm the functionality of the proposed system that offers an effective solution for night-time traffic surveillance and intelligent transportation management.

conclusion

In this work, we proposed a Hybrid Attention-Driven Recurrent Neural Network (HADRNN) for the purpose of sentiment classification of social media texts. To do so, it combines CNN-based local feature extraction, Bi-GRU sequential modelling and a multi-level attention mechanism to model for phrase-level cues, long range dependencies and sentiment critical tokens jointly. With soothing these complementing weapons, the frame handles the difficulties associated with weathered terminology, situational ambiguity and noisy information that are present in social media streams efficiently. The proposed HADRNN outperformed the baseline CNN-, LSTM- and Transformer-based methods on benchmarks like Twitter Sentiment140 and IMDB reviews, demonstrated through experiments. On Twitter Sentiment140 the model gave 92.1% accuracy and 91.3 F1-score while it achieved 94.6% accuracy and 94.1% F1-score on IMDB which indicates that the trained model generalizes well with respect to both short, context-rich posts, as well as long review-style documents. This not only provided better classification performance but also introduced interpretability since it identified sentiment-rich expressions. (i) The design of a hybrid deep learning framework for sentiment classification that integrates convolutional, recurrent, and attention mechanism, (ii) Empirical results showing consistent performance improvements in various types of heterogeneous datasets for the same task and (iii) A new method to provide interpretability about model decisions. Despite these advances, limitations remain. It is a highly computationally intensive process to train the model, making real-time processing at scale of millions of posts per seconds infeasible. While attention would improve the interpretability, it is not always sufficient to fully explain how decisions are being made by Deep Neural Nets. Future work will focus on lightweight variants of the HADRNN to be deployed on edge devices, integration with pre-trained transformer embeddings for deeper semantic enrichment and adapting it for multimodal sentiment analysis across text, images and audio. These guidelines are intended to broaden the utility of the framework to a wider range of applications in real-world analytics contexts like doing things such as automating customer service, detecting and monitoring political sentiment, misinformation detection and so on.

References

[1] P. Gururama senthilvel et al, “an enhanced deep learning approach for intelligent healthcare emotion analysis using facial expressions and feature analysis to identify pain”, robotica, april 2025, published by cambridge university press.
[2] P. Gururama senthilvel et al, “energy-efficient and secure routing in iot-wsns using adaptive clustering and trust-based mechanisms”, information security journal: a global perspective, march 2025.
[3] Innan, N., Khan, M. A. Z., Marchisio, A., Shafique, M., & Bennai, M. (2024, June). Fedqnn: Federated learning using quantum neural networks. In *2024 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-9). IEEE.
[4] Annan, R., Noland, J., Perkins, K., Yuan, X., Roy, K., & Qingge, L. (2025). Genomic privacy and security in the era of artificial intelligence and quantum computing. *Discover Computing*, *28*(1), 108.
[5] Marengo, A., & Santamato, V. (2025). Quantum algorithms and complexity in healthcare applications: a systematic review with machine learning-optimized analysis. *Frontiers in Computer Science*, *7*, 1584114.
[6] Gupta, K., Saxena, D., Rani, P., Kumar, J., Makkar, A., Singh, A. K., & Lee, C. N. (2024). An intelligent quantum cyber-security framework for healthcare data management. *IEEE Transactions on Automation Science and Engineering*.
[7] Priyaa, N.V., TamilSelvan, S.(2025) Comparison of improved XGBoost algorithm with random forest regression to determine the prediction of the mobile price, Applications of Mathematics in Science and Technology International Conference on Mathematical Applications in Science and Technology, pp. 626–629, eBook ISBN9781003606659
[8] Sireesha, M., Tamilselvan, S.(2024) Detecting Fake Political News on Social Media by Support Vector Machine Compared to Naive Bayes 2024 2nd International Conference Computational and Characterization Techniques in Engineering and Sciences Ic3tes 2024, DOI: 10.1109/IITCEE59897.2024.1046802.
[9] Chow, J. C. (2025). Quantum computing and machine learning in medical decision-making: a comprehensive review. *Algorithms*, *18*(3), 156.
[10] Guo, Y., Gao, Y., & Song, J. (2024). Molcfl: A personalized and privacy-preserving drug discovery framework based on generative clustered federated learning. *Journal of biomedical informatics*, *157*, 104712.
[11] Probul, N., Bakhtiari, M., Kazemi Majdabadi, M., Orbán, B., Fejér, S., Das, S., ... & Baumbach, J. (2023). Newest Advances on the FeatureCloud Platform for Federated Learning in Biomedicine. In *4th Belgrade Bioinformatics Conference* (Vol. 4, pp. 49-49). Belgrade: Institute of molecular genetics and genetic engineering.
[12] Nasajpour, M., Pouriyeh, S., Parizi, R. M., Han, M., Mosaiyebzadeh, F., Liu, L., ... & Batista, D. M. (2025). Federated Learning in Smart Healthcare: A Survey of Applications, Challenges, and Future Directions. *Electronics*, *14*(9), 1750.
[13] Bashir, A. K., Victor, N., Bhattacharya, S., Huynh-The, T., Chengoden, R., Yenduri, G., ... & Liyanage, M. (2023). Federated learning for the healthcare metaverse: Concepts, applications, challenges, and future directions. *IEEE Internet of Things Journal*, *10*(24), 21873-21891.
[14] Alzakari, S. A., Sarkar, A., Khan, M. Z., & Alhussan, A. A. (2024). Converging technologies for health prediction and intrusion detection in internet of healthcare things with matrix-valued neural coordinated federated intelligence. *IEEE Access*, *12*, 99469-99498.
[15] Smajić, A., Grandits, M., & Ecker, G. F. (2023). Privacy-preserving techniques for decentralized and secure machine learning in drug discovery. *Drug Discovery Today*, *28*(12), 103820.
[16] Ewejobi, P., Okokpujie, K., Adetiba, E., & Alao, B. (2024, April). Homomorphic Encryption for Genomics Data Storage on a Federated Cloud: A Mini Review. In *2024 International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG)* (pp. 1-13). IEEE.
[17] Rajasekaran, R. T., & Selvam, M. (2025). AI-Powered Behaviour Analysis in Financial Services. In 2025 International Conference on Data Science, Agents & Artificial Intelligence.
[18] Kalpana K, Paulchamy B ,Stephen Jeswinde Nuagah, Piyush Kumar Shukla., “Design of a high-performance advanced phase locked loop with high stability external loop filter”, IET Circuits Devices Systems,17(1), 1– 12,(2023).
[19] M Selvam et al, “AI-Powered Behaviour Analysis in Financial Services”, 2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI).
[20] M Selvam et al, “Enhancing User Interaction in Digital Financial Systems Using AI-Driven Front-End Technologies: A Personalised Response Approach”, 2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI).