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Hierarchical Learning Models for Generalization Across Heterogeneous Data

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Abstract
The importance of automated surveillance technologies in terms of surveillance of traffic intelligence has been significantly increased within smart cities, as the technologies allow for traffic analysis, traffic congestion management, accident detection, and efficient traffic control. Nevertheless, contemporary traffic surveillance methods usually encounter problems such as inefficient traffic detection, lack of robustness in changing traffic environment, and inadequate data privacy protection, hindering their applications in practical cases in the area of large-scale smart cities. With regard to the problems mentioned above, a model of privacy-preserving intelligent traffic surveillance method utilizing Hunger Games Search-optimized Faster Region-based Convolutional Neural Networks (HGS-Faster R-CNN) is presented in the paper. It is suggested that the HGS-Faster R-CNN model can be able to enhance privacy-preserving traffic surveillance by determining the best hyperparameters of Faster R-CNN utilizing the principles of HGSO. The evaluation process can be performed based on a traffic surveillance privacy dataset. The pre-processing phase makes use of Gabor filters to improve the quality of the images obtained and highlight edges and texture information. Following this, feature extraction by the Histogram of Oriented Gradients (HOG) technique is done to extract motion and structural features of the objects while protecting user privacy. From the experimental outcomes, the developed model shows high accuracy levels of 98.3%, high recall rate of 98%, and F1-score of 98.29%. This model is superior to other models since it can detect traffic objects efficiently at a lower detection latency period. The implementation of the model involves the use of programming languages such as Python, TensorFlow, Keras, OpenCV, and CUDA. In general, the proposed model proves to be effective, scalable, and privacy-preserving, thus becoming quite appropriate for real-world smart city traffic surveillance applications.

Keywords: Automated surveillance systems, Urbanization, Monitoring Traffic, Histogram of Oriented Gradients (HOG), Smart Cities.

1. Introduction

Urbanization, increase in population size, and increasing number of vehicles have led to increased road accidents, thereby putting a lot of pressure on transport systems and policies within urban areas. At the same time, changing population dynamics necessitate continuous modifications to urban infrastructure to meet evolving societal and mobility demands [1]. Because of urbanization, traffic congestion is common nowadays, which results in economic inefficiencies and reduced quality of life. To address this challenge, smart cities have adopted Machine Learning (ML), Artificial Intelligence (AI), and Internet of Things (IoT), technologies that has the ability to help to enhance urban transport by means of predicting traffic [2]. Intelligent Transportation Systems (ITS) endeavor to achieve optimal smart traffic light control and route planning through monitoring and scheduling. Traditional approaches, such as fixed cycle or rule-based approaches, cannot adapt to changes in traffic flow and unforeseen incidents [3]. Traffic forecasting helps governments adjust traffic light schedules, control the use of roads, and organize diversion in case of emergencies. Traffic forecasting also aids navigation systems in recommending the best route possible [4]. Urban signal operate using fixed time intervals, which are unable to adapt to fluctuating traffic conditions. As a result, they often cause increased vehicle waiting times, traffic congestion, and inefficient energy utilization. Therefore, intelligent adaptive traffic management systems are required to overcome these limitations and improve overall traffic flow efficiency [5]. The emissions from vehicles include nitrogen oxides, particulate matter, and carbonmonoxide, negatively impact air quality and contribute to smog formation. Traffic management plays a vital function in safety, commuter convenience, and air quality in smart cities [6].

Research Aim: The main objective is to develop an automated privacy-preserving smart traffic surveillance system regarding smart city using a Hybrid Hunger Games Search-optimized Faster Region-Based Convolutional Neural Network (HGS-Faster R-CNN) approach integrated with Gabor filtering and Histogram of Oriented Gradients (HOG).

Research Organization: Section 1 provides the introduction to intelligent traffic surveillance systems and their background. Section 2 contains an overview of prior works on smart city traffic surveillance. Section 3 elaborates on the methodology. Section 4 shows the performance evaluation and its discussion, and Section 5 depicts conclusion.

2. Related work

Research [7] proposed the Secretary Bird Optimization-based Multipath Routing Protocol (SBOMRP) to enhance energy efficiency and congestion control in parallel routing paths for Wireless Sensor Networks (WSNs) inside smart city environments. It improves performance by achieving a 5-9% higher network lifetime, an 18% increased throughput, and a 14% improved Packet Delivery Ratio (PDR) compared to the Virtual Hierarchical Forwarding Routing Protocol (VHFRP). The Federated Learning-based Predictive Traffic Management (FLPTM) model [8], incorporating the Contained Privacy-Preserving Scheme (CPPS), enhances prediction performance, privacy preservation, and overall efficiency in Intelligent Transportation Systems (ITS), thereby supporting the operation of Autonomous Vehicles (AVs). According to simulation results, the proposed method achieves a 23.3% reduction in communication cost, a 16.1% reduction in the impact of adversarial attacks, and an 18.95% improvement in access speed. The Periodicity-Aware Dynamic Relational Spatio-Temporal Graph Convolutional Network (PDR-STGCN) model was proposed for traffic flow forecasting by capturing periodic patterns and dynamic spatial dependencies among urban road networks. This model performs better and provides a 16.5% improvement in Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) 9%. But this model evaluation is performed on only three datasets, which makes it less generalized to traffic situations of various types [9]. Research [10] carried out an investigation on the prediction of traffic flow for adaptive traffic control by applying ML and DL such as Multi-Layer Perceptron Neural Networks (MLP-NN), Recurrent Neural Networks (RNNs), and Gradient Boosting. The MLP-NN provided R^2 and EV of 0.93. But this model is limited to predicting traffic flows only and does not cover all traffic management and control concerns. Optimization of urban traffic control was achieved through Artificial Intelligence (AI), Reinforcement Learning (RL), predictive analytics, Graph Neural Network (GNN), Long Short-Term Memory (LSTM), and AutoRegressive Integrated Moving Average (ARIMA) [11]. These results indicate a decrease waiting time by 33% and a decrease emissions by 16%. Nevertheless, the system's ability to work adaptively in case of extraordinary situations, such as massive gatherings of people or negative weather conditions, remains unverified. Research presented in [12] focuses on the efficiency of the adaptive approach to managing traffic by means of IoT using multi-agent simulation, predictive analytics, and integration of sensor data, leading to a 30% increase in urban mobility, a 50% decrease in traffic jams, and a 28% decrease in CO_2 emissions in a simulated traffic-only environment. The Visual Auxiliary Graph Neural Network (VA-GNN) algorithm introduced in [13] indicates its suitability for use in ITS with the Area Under the Curve (AUC) of 0.673, F1-score 0.487, and accuracy of 0.556, although being rather ineffective when predicting future events. Fusion-based Intelligent Traffic

Congestion Control System for Vehicular Networks (FITCCS-VN) system proposed in [14] uses artificial intelligence in the form of ML to optimize the traffic system of smart cities and minimize congestion, and it has been shown that the algorithm is 95% accurate with a 5% failure rate. Research [15] proposed a traffic monitoring system for smart city derived from the deep learning using You Only Look Once version 5 (YOLOv5), MobileNet-v1-SSD, Faster RCNN, and Convolutional Neural Networks (CNN) the in an embedded system, with 90% precision and 66% recall rate in less than 10 milliseconds. In addition, the Attention Module-Multi-modal Feature Fusion GoogLeNet (AM-MMFF-GoogLeNet) architecture [16], which has been designed for detecting vehicles, was capable of achieving 97.6% accuracy and maintaining an impressive 95.5% accuracy even when the circumstances change, in less than 20.5 ms.

3. Methodology

Privacy-preserving automated system of surveillance regarding smart traffic monitoring in cities. The architecture of the proposed privacy-preserving automated surveillance system for intelligent traffic monitoring is depicted in Fig. 1. The Gabor filtering improves the quality of an image by enhancing its edges and texture. The HOG algorithm detects the motion and structural information without compromising on the privacy of the users. The Faster R-CNN model conducts vehicle detection and localization.

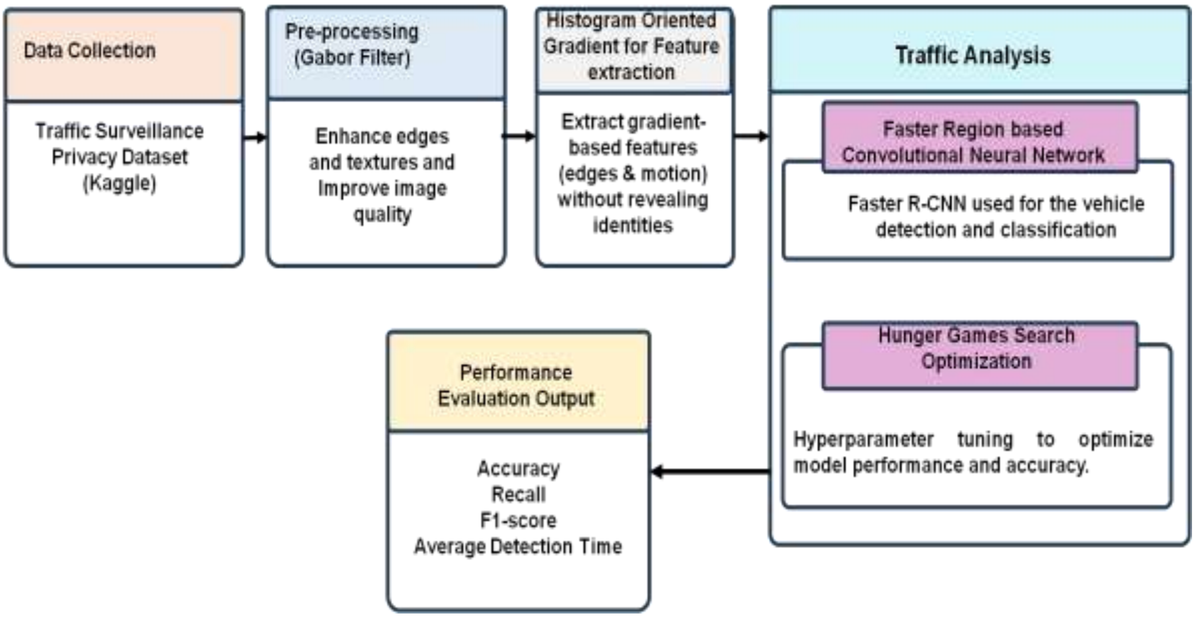


Figure 1: Methodology flow of HGS-Faster R-CNN

3.1 Data Collection

The smart traffic surveillance system would make use of the traffic surveillance privacy dataset kaggle (https://www.kaggle.com/datasets/yusufberksardoan/traffic-detection-project), to enable automatic traffic detection without violating the privacy of individuals. The dataset consists of 6,633 labeled images that are systematically classified in the ratio of 5,805 images for the training data set, 549 images for the validation data set, and 279 images for the test data set. The partitioning is key to the development of a strong model, proper hyperparameter tuning, and accurate performance evaluation under different traffic conditions.

3.2 Data Preparation

A **Gabor filter** is used to improve the quality of traffic surveillance images. Gabor filters are linear filters that are selective based on frequency and orientation and give prominence to edges and textures. With the help of Gabor filters, one can highlight edges and textures related to vehicles, roads, etc., which results in better discrimination between vehicles and background. Therefore, Gabor filters play an important role in image pre-processing, which helps in detecting vehicles and analyzing traffic in smart cities.

$\mathrm{Filt_{image}} - \mathrm{Np.abs}\ (\mathrm{Gab}(\mathrm{Gry_{image}}. \mathrm{Freq} = \mathrm{Freq}, \mathrm{theta} = \mathrm{theta}, \mathrm{sig_w} = \mathrm{sig_w}, \mathrm{sig_z} = \mathrm{sig_z})$ (1)

In Equation (1), $\mathrm{Filt_{image}}$ denotes the image of the traffic filtered,abs refers to the absolute function,Np refers to the NumPy library, Gab denotes the function of gabor filter, $\mathrm{Gry_{image}}$ denotes the input image of grayscale, Freq refers to the frequency value of the filter, theta denotes the orientation angle of the filter, and $\mathrm{sig_w}$ and $\mathrm{sig_z}$ denote the parameters of horizontal and vertical spread.

$\mathrm{Filt_{image}} = (\mathrm{Filt_{image}} - \mathrm{NP.min}_{(\mathrm{Filt_{image}})})/(\mathrm{NP.max}_{(\mathrm{Filt_{image}})} - \mathrm{NP.min}_{(\mathrm{Filt_{image}})}) * 255$ (2)

In Equation (2),$NP.\min_{(Filt_{image})}$ and $NP.\max_{(Filt_{image})}$ represent the minimum and maximum intensity of the pixels, $Filt_{image} - NP.\min_{(Filt_{image})}$ refers to the shift operation of the intensity, and $(NP.\max_{(Filt_{image})} - NP.\min_{(Filt_{image})})$refers to the range normalization intensity.

The Histogram of Oriented Gradients (HOG) is the feature extraction method stands highly effective for traffic monitoring in smart cities, as it utilizes gradient magnitudes and orientation information to accurately detect and classify vehicles, roads, and pedestrians while preserving individual privacy by focusing on structural features rather than personal identity information. The frames from the traffic surveillance privacy dataset are segmented into cells and blocks, and then gradient calculations and normalization are performed. The features extracted contain the edges and motions of objects without exposing their identities.

$$\nabla y(l,b) = \begin{bmatrix} y(l,b+1) - y(l,b-1) \\ y(l+1,b) - y(l-1,b) \end{bmatrix} \quad (3)$$

In Equation (3), the notation of $y(l,b)$ is the intensity of a particular pixel located at (l,b)on an imaging frame, $\nabla y(l,b)$representing the gradient vector that helps in determining edges and motion cues concerning vehicles and roads. l, $l+1$, and $l-1$stand for present, future, and past horizontal pixel coordinate.b, $b+1$, and $b-1$denote the present, future, and past vertical pixel coordinate,g denotes the value of pixel intensity, and ∇denotes the gradient operator.

$$|\nabla y| = \sqrt{v_l^2} + v_b^2 \quad (4)$$

$|\nabla y|$represents the gradient magnitude that is employed to quantify edge strength in traffic images, $v_l^2$and v_b^2 are the variations in intensity along the horizontal and vertical directions, respectively, and v denotes the difference of the gradient intensity.

$$\theta = \tan^{-1}(\frac{v_l}{v_b}) \quad (5)$$

In equation (5), θ is the angle at which the gradient is oriented, $\tan^{-1}$ refers to the inverse of the tangential function,and$\tan^{-1}(\frac{v_k}{v_a})$refers to the function of the gradient direction. Figure 2 depicts the urban traffic scene analysis, including the original input, conversion to grayscale, and the feature map analysis, which is useful in learning spatial patterns in object detection and scene understanding in urban settings.

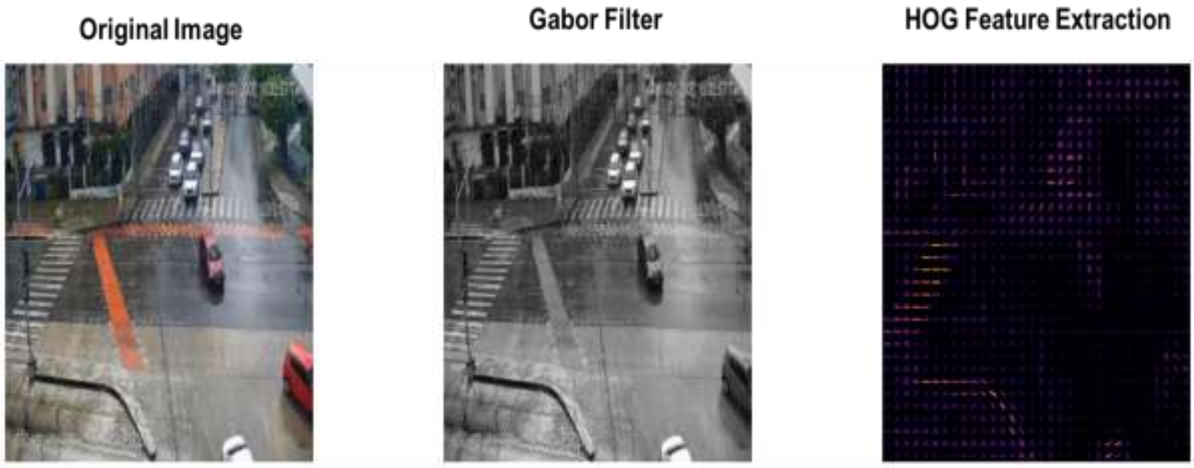


Figure 2: Feature Analysis of Traffic monitoring

3.3 Intelligent Traffic Monitoring in Smart Cities

Privacy-Preserving automated system of surveillance for intelligent traffic congestion monitoring in smart cities uses a combination of Faster R-CNN and HGSO to optimize vehicle and traffic object classification and analysis. Faster R-CNN is used to accurately and quickly detect vehicles and traffic objects using surveillance video frames. The CNN pre-training technique is applied to extract the required convolutional features, while the RoI layer pools regions to convert them into feature vectors to enable classification and localization. The HGSO algorithm is used to optimize hyperparameters to enhance detection efficiency.

Faster Region-based Convolutional Neural Network (Faster R-CNN): The Faster R-CNN model shown in Figure 3 is used for the detection of vehicles in traffic surveillance systems. The Faster R-CNN method offers improved detection accuracy and speed, in comparison with regular R-CNN methods, thereby allowing the model to process traffic surveillance videos effectively. The input frames are first fed into a pre-trained CNN model that computes the convolutional features of the image. To convert the variablesized regions of interest to feature vectors, a RoI pooling layer is used. Each region of interest generates the softmax probability values and offsets of the detected object.

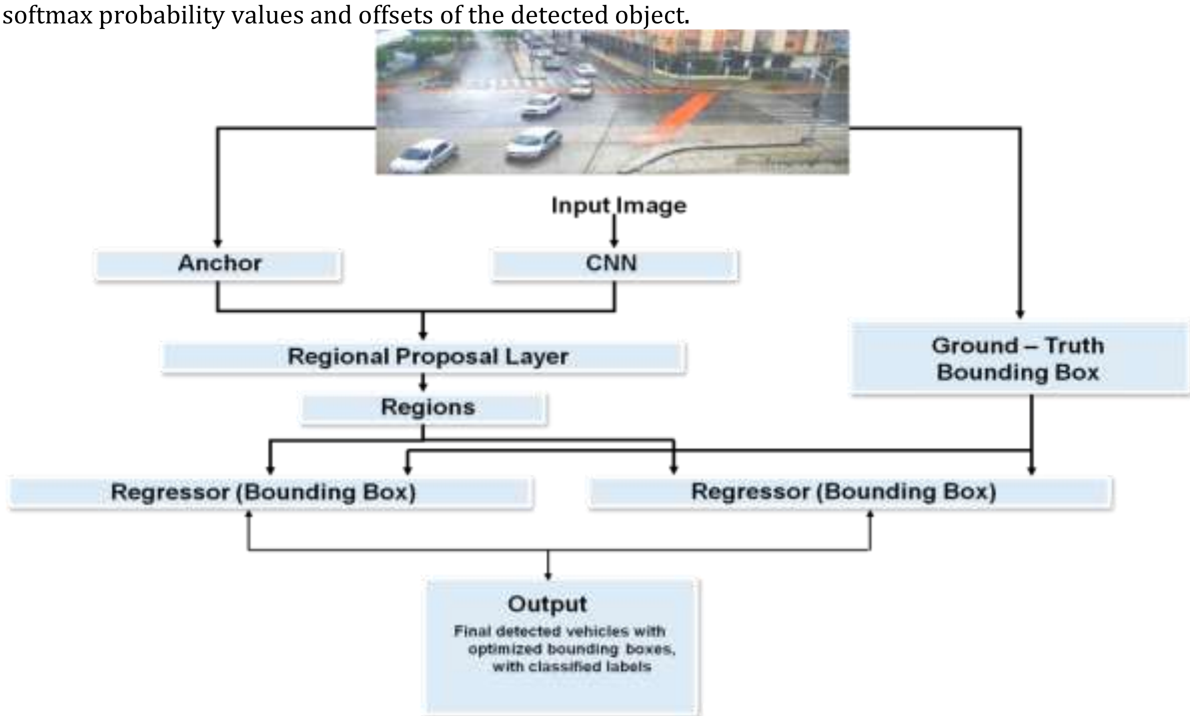


Figure 3: Architecture of Faster RNN

Hyperparameter tuning with Hunger Games Search optimization (HGSO): In the design of the privacy-preserving automated system of surveillance with regard to intelligent vehicle traffic movement monitoring in smart cities, the proposed HGSO technique maximizes system's resource efficiency of the through the dataset. The HGSO technique mimics the natural process of animals' search for food, and thus it can make an effective tradeoff between exploration and exploitation. First, various solutions are produced, and then the fitness of each solution is assessed according to traffic surveillance image data.

$$\mathrm{W} = \begin{cases} \mathrm{W(s)} \times (1 + \mathrm{rand}), \mathrm{q_1} < \mathrm{k} \\ \mathrm{X_1} \times \mathrm{W_a} + \mathrm{Q} \times \mathrm{X_2} \times |\mathrm{W_a} - \mathrm{W(s)}|, \mathrm{q_1} > \mathrm{k}, \mathrm{q_2} > \mathrm{F} \\ \mathrm{X_1} \times \mathrm{W_a} - \mathrm{Q} \times \mathrm{X_2} \times |\mathrm{W_a} - \mathrm{W(s)}|, \mathrm{q_1} > \mathrm{k}, \mathrm{q_2} < \mathrm{F} \end{cases} \tag{5}$$

In Equation (5), W denotes the vector of the Surveillance solution, W(s)and $\mathrm{W_a}$denote the state of the current and best surveillance solution,randdenotes the factor of the random exploration, $\mathrm{q_1}$ and $\mathrm{q_2}$ are the control parameters of random distribution, k refers to the value ofthreshold, $\mathrm{X_1}$and $\mathrm{X_2}$ denote the solution of candidate update and measure of distance,Qrepresents the coefficient of random control, F represents the control factor of convergence, and $|\mathrm{W_a} - \mathrm{W(s)}|$ denotes the difference of performance.

$$Q = 2 \times t \times rand - t, t = 2 \times (1 - \frac{s}{S}) \tag{6}$$

In Equation (6),Qrepresents the coefficient of random control,$rand$denotes the factor of the random exploration,t denotes the control parameter of search, s denotes the count of the present iteration, S denotes the limit of maximum iteration, and$1 - \frac{s}{S}$denotes the factor iteration decay.

$$F = sech(|Fit_j - Fit_a|) \tag{7}$$

In Equation (7),F represents the control factor of convergence,$sech$ represents the function of hyperbolic secant, Fit_j and Fit_a denote the fitness of the current and best solution, and $|Fit_j - Fit_a|$ represents the difference in fitness measure.

$$X_2 = 2(1 - f^{(-|G_j - TG|)}) \times q_5 \tag{8}$$

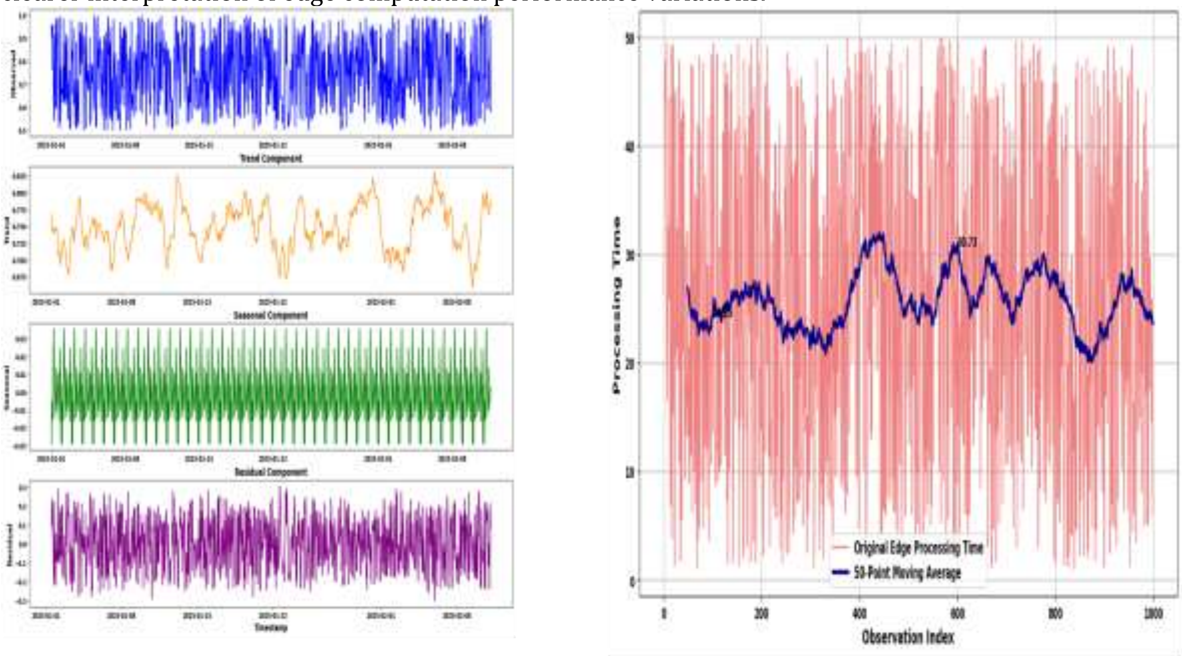
In Equation (8),X_2 denotes themeasure of distance,f denotes the function of Exponential, G_j denotes the value of current entropy, TG denotes the secure value of hash, $|G_j - TG|$ refers to the difference of entropy method, and q_5 denotes the factor of random scaling.

Hyperparameter of the suggested model: Faster R-CNN architecture can be tuned to use optimized hyperparameters enhances prediction accuracy made from traffic conditions and stability concerning training process. The learning algorithm used for the optimization of the network is Adam, with the rate of learning set to 0.0001. The learning raining pipeline is conducted with the aim of 100 epochs over a batch size of 16 and uses the Rectified Linear Unit (ReLU) and the function of Cross-Entropy loss.

4. Result

With regard to testing purposes, intelligent traffic monitoring system was developed in a high-end computing system to guarantee effective training and reliable surveillance analysis. It was deployed with Intel Core i7 computer with an NVIDIA RTX 3080 graphics card, 32 GB of RAM, and 1 TB SSD. The software tools used were Windows 11, Python 3.10, TensorFlow 2.12, Keras 2.12, CUDA 11.8, OpenCV 4.8, and NumPy 1.24.

Explorative Data Analysis: The process of traffic signals' decomposition and the edge processing performance evaluation is shown in Figure 4. Figure 4(a) provides the procedure for traffic signal decomposition, whereby traffic signals are decomposed into four types of traffic signals, namely original signals, trend signals, seasonal signals, and residual signals. This is done to make the time series analysis effective and help unearth any traffic patterns within the analyzed traffic signals. Figure 4(b) compares the original and smoothed edge processing times. While the original processing time shows large fluctuations across observations, the 50-point moving average produces a stable trend, reducing noise and enabling clearer interpretation of edge computation performance variations.



(a) (b)

Figure 4: Visualization of (a) Decomposition of Traffic Data, and (b) Comparison of Edge Processing Times

Evaluation Metrics: Accuracy is the measure of the overall correctness of the predictions made for traffic monitoring, keeping surveillance privacy intact. Recall is used as a measurement parameter of the ability of the algorithm to correctly detect traffic events without omitting any crucial surveillance data. F1-Score finds the balance between precision and recall for assessing detection performance while guaranteeing surveillance privacy. Average Detection Time ensures processing time for facilitating dynamic intelligent traffic surveillance and decision-making processes.

Performance Evaluation: Comparing the deep learning models shown in Figure 5 and Table 1, there is an incremental improvement in the performance of detection accuracy. Models such as Multi-Task GoogLeNet(MT-GooGLeNet) [16], Caffe-based convolutional network (CaffeNet) [16], and Visual Geometry Group Network (VGGNet)[16] have average accuracy and higher detection times. Models like Residual Network with 50 layers (ResNet-50) [16], EfficientNet-B3 [16], and EfficientNet-B7 [16] improve on accuracy and time efficiency, while transformer models like DEtectionTRansformer (DETR)[16] and Swin Transformer [16] provide good accuracy along with better feature representation. The AM-MMFF-GooGLeNet [16] model provides competitive results by improving accuracy and time efficiency. The proposed HGS-Faster R-CNN model performs the best with 98.3% accuracy and the lowest detection time of 26.9 ms.

Table 1: Baseline Models comparison with the HGS-Faster RCNN Model

Model	**Avg. Detection Time** (**ms**)	**F1 − score** (%)	**Recall** (%)	**Accuracy** (%)
MT − GooGleNet [16]	41.2	93.8	93.2	94.5
CaffeNet [16]	48.7	91.7	91.4	92.1
VGGNet [16]	47.5	93.3	92.9	93.7
ResNet − 50 [16]	36.4	96.0	95.7	96.3
EfficientNet − B3 [16]	30.1	96.8	96.5	97.2
EfficientNet − B7 [16]	28.3	97.1	96.8	97.5
DETR [16]	34.7	97.5	97.2	97.9
Swin Transformer [16]	28.9	97.3	97.0	97.7
AM − MMFF − GooGleNet [16]	27.6	97.8	97.5	98.1
HGS − Faster R − CNN [**Proposed**]	26.9	98.29	98.00	98.3

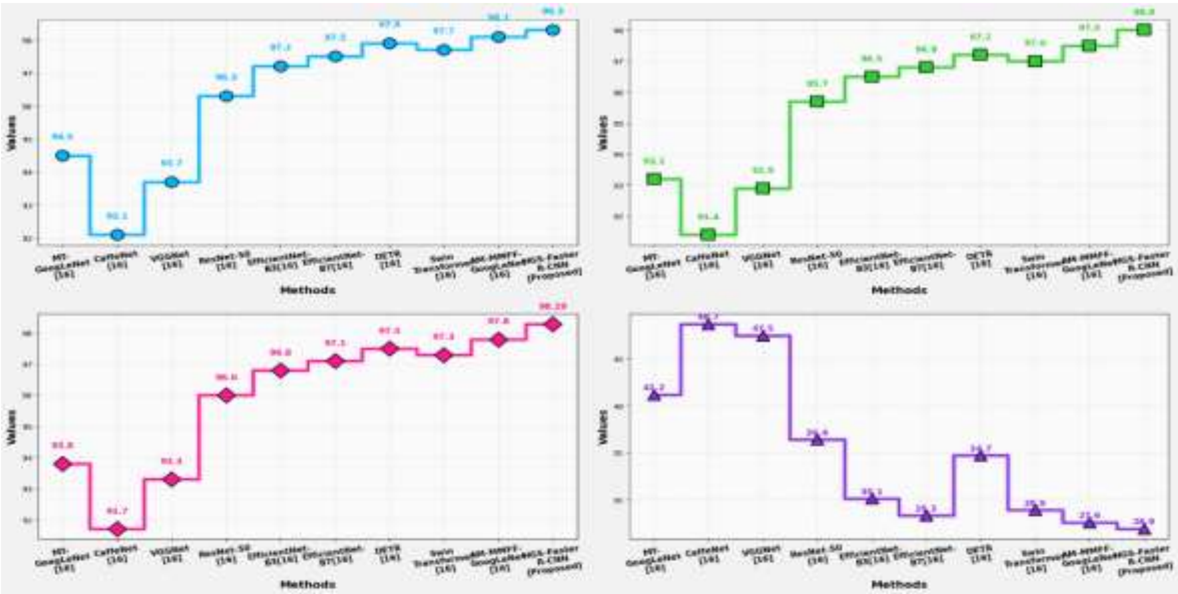


Figure 5: Performance Comparison of the Existing Methods

The baseline models are retrained using the traffic surveillance privacy dataset on the same experimental setups and train-test splits for a level playing field, as shown in Table 2. All the models were subjected to similar pre-processing techniques, such as Gabor Filtering and feature extraction using HOG features. The metrics used to assess the metrics include average time taken to detect vehicles, Recall, Accuracy, and F1-Score. Experimental findings clearly validate in which the suggested HGS-Faster RCNN performs better than the DL model regarding detection F1-score, accuracy, average detection time, and Recall.

Table 2: Retrained Results of the Baseline Models with the Proposed Architecture

Model	**Avg. Detection Time** (**ms**)	**F1 − score** (%)	**Recall** (%)	**Accuracy** (%)
MT − GooGleNet	42.6	93.0	92.4	93.8
CaffeNet	49.8	90.5	90.2	91.0
VGGNet	48.9	92.4	92.1	92.9
ResNet − 50	37.8	95.0	94.6	95.4

$\boldsymbol{Model}$	$\boldsymbol{Avg. Detection\,Time}$ $(\boldsymbol{ms})$	$\boldsymbol{F1 - score}$ (%)	$\boldsymbol{Recall}$ (%)	$\boldsymbol{Accuracy}$ (%)
$EfficientNet - B3$	31.5	96.0	95.7	96.4
$EfficientNet - B7$	29.6	96.5	96.2	96.9
$DETR$	35.9	96.9	96.6	97.2
$Swin\,Transformer$	30.2	96.7	96.4	97.0
$AM - MMFF - GooGleNet$	28.4	97.3	97.0	97.6
$HGS - Faster\,R - CNN\,(Proposed)$	26.9	98.29	98.00	98.3

Discussion: Comparison indicates that deep learning algorithms gradually enhance the accuracy, recall and F1-score, while minimizing the detection time in complicated detection scenarios. The MT-GooGleNet [16] algorithm possesses inadequate features and higher detection time, while the CaffeNet [16] algorithm exhibits outdated architecture and low generalization capacity. The VGGNet [16] algorithm consumes much computational power and is slower in making predictions, and the ResNet-50[16] algorithm is relatively heavy, despite its better results. EfficientNet-B3 [16] is efficient, although it does not possess good robustness, whereas the EfficientNet-B7 [16] algorithm is characterized by extremely high computational cost. The DETR [16] algorithm needs much training data and takes too long to converge, while the Swin Transformer [16] algorithm is resource-consuming and complicated. The AM-MMFF-GooGleNet [16] algorithm is accurate, but it retains certain drawbacks of CNN algorithms, together with additional complications. To overcome all the drawbacks of all the approaches, HGS-Faster R-CNN gives excellent results compared to all previous solutions. The approach gives better accuracy, a better F1-score, and reduced time taken to detect objects. The technique overcomes the weaknesses of both CNN-based and transformer-based approaches.

5. Conclusion

The research proposes an automated surveillance system based on intelligent traffic management in smart cities through Gabor filtering, HOG features, and optimization of HGS-Faster R-CNN. The proposed methodology effectively improves the accuracy of vehicle detection, minimizes the delay in computations, and efficiently analyzes traffic under different urban conditions. Experiments conducted on the traffic surveillance privacy dataset show that the proposed HGS-Faster R-CNN has achieved the best results with an accuracy of 98.3%, recall of 98.00%, F1-score of 98.29%, and average detection time of only 26.9 ms. The system perform poorly during harsh weather conditions, occlusions, and dense traffic due to the lack of proper feature representation of the context. Future research activities can incorporate multimodal sensor fusion techniques, together with a light-weight transformer model for increasing performance levels.

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