ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN:2454-9940 www.ijsem.org
Vol 20, Issuse.2 April 2026

Integrated Recognition Approach And Fining System Towards Detection And Tracking Of Traffic Violating Multiple Vehicles Using Pairing Net And Light Weight Deep Sort Fast Yolo Rec Architectures

[1]KEERTHI SRIVARDHAN,[2]MUDAM MANISH,[3]PATHA SHIVA SAI,[4]Dr.C.Sasikala,

[1,2,3] Student,Department of EEE,Narsimha Reddy Engineering College,Misammaguda(V),Kompally-500100,Telangana State,India.
[4]Professor,Department of EEE,Narsimha Reddy Engineering College,Misammaguda(V),Kompally-500100,Telangana State,India.

ABSTRACT

Thanks to advancements in intelligent transport management systems, computer vision and traffic monitoring sensors can now better identify vehicles that aren't acting normally. Overspeeding, overloading, helmet violations, frequent lane changes, fake or unrecognized license plates, and multi-vehicle recognition and tracking in shifting traffic are areas where current techniques fall short. To enhance detection efficiency and speed, this research study suggests a self-driving fining system and end-to-end recognition approach based on PairingNet + Lightweight Deep SORT Fast YOLO-Rec Architecture. Processing into frames is done using real-time sensor data obtained from benchmark datasets or live video feeds. Utilizing a Convolutional Neural Network (CNN) backbone with Residual Blocks, Dark Blocks, and Cross-Stage Partial (CSP) Connection Blocks, Fast YOLO-Rec extracts the multi-scale features. Even when dealing with objects of varying sizes, Path Aggregation Network (PANet) detection remains accurate. An anchor box prediction approach creates bounding boxes for tracking, while a graph convolution network-based method called PairingNet links cars between frames using similarity in contour and texture. Offenses like as overloaded vehicles, helmet abuse, and fraudulent license plates are classified using the Deep SORT algorithm. When violations are found, alerts are sent to the appropriate authorities and the vehicle's owner. The experimental findings demonstrate that the proposed model outperforms conventional approaches in terms of processing efficiency and detection accuracy, providing a reliable answer to the problems of traffic enforcement and road safety.

Keywords: Vehicle Monitoring, Vehicle Detection, Vehicle Classification, Number Plate Classification, Number of rider detection, Fast Yolo Rec Algorithm, Automated Fining, Convolution Neural Network.

INTRODUCTION

traffic parameters in order to decrease the number of traffic offenses. Thanks to recent developments in AI and sensor technology, an integrated and coordinated network has been developed to determine vehicle abnormalities on roadways and offer analytics solutions to commuters in the form of real-time insights on organized traffic data of their preferred destinations. This intelligent traffic management system is both effective and efficient. Due to a combination of factors, including a dense population and unpredictable traffic flows involving a wide range of vehicle sizes and types, developing nations like India continue to face significant challenges in the detection and tracking of traffic violations, despite the numerous technological advancements made in this area.
Several traffic violations, including vehicle racking,

ISSN:2454-9940 www.ijsem.org
Vol 20, Issuse.2 April 2026

vehicle overspeeding, vehicle overloading, driving without helmets, frequent lane changes, fake numbers, and non-recognized number plate usages, can be detected, tracked, and automatically fined with the help of a new solution called Pairing Net + Light Weight Deep Sort Fast Yolo Rec Architecture. Intelligent transportation systems are essential for urban traffic management worldwide because they offer utilities to evaluate these issues. Along with helping vehicles and their beneficiaries with traffic offenses at their desired locations, the proposed model may recognize various types of vehicles that violate traffic regulations with better identification accuracy and detection speed. A specific design makes use of sensor data gathered by the base station or stored in the benchmark dataset repositories of the relevant government or insurance organizations in the designated areas or desired locations.

The remainder of the article is organized into sections as follows: section 2 comprises a literature review on intelligent transportation system architecture with a focus on vehicle detection and tracking of violations, and section 3 details the design of the current pairing net + light weight deep sort fast yolo rec architecture in relation to video data obtained from government repositories. In Section 4, we compare the proposed method's experimental results with those of the traditional intelligent transportation architecture using the aforementioned metrics for detection speed and accuracy.

RELATED WORKS

Improved traffic monitoring, safety regulation, and forecasting analysis have resulted from the increasing usage of computer vision and deep learning in smart transportation systems. The research included in this literature review range from those pertaining to traffic flow forecasting and vehicle speed detection to those pertaining to safety features like driver phone use monitoring and helmet use detection. 2017 [11] enhanced real-time enforcement by improving automatic helmet identification using deep learning. Using YOLO and OpenCV for enhanced surveillance, Jyothis et al. (2024) [4] applied deep learning to railway safety. Intelligent transportation technology is adaptable, and this project shows that it may be used in ways that aren't limited to conventional roads. The reviewed literature shows that computer vision and deep learning have reached a mature stage in intelligent transportation and traffic safety. These accomplishments, which range from traffic prediction to helmet identification, highlight the significance of an infrastructure built on AI-based solutions for improved enforcement, monitoring, and accident prevention.

In order to organize transportation efficiently, traffic flow forecasting is crucial. A large data-based deep learning approach for accurate traffic flow prediction is proposed by Lv et al. (2015) [1]. More recently, a deep learning method for improving the accuracy of network-wide speed propagation forecasts was introduced by Yang et al. (2023) [14]. This method relies on dependencies and dynamics. To improve their capacity for making short-term predictions, Bharti et al. (2023) [15] also used a PSO-Bi-LSTM model to optimize traffic forecasting. An early use of computer vision technologies was developed by Wu et al. (2009) [2], who created an algorithm for autonomous vehicle speed detection using video-based analysis. The use of mobile phone use detection from high-occupancy vehicle photos for safety regulation enforcement was expanded by Artan et al. (2014) [3] to driver monitoring. There has been a lot of study on motorcycle safety, and deep learning has been particularly useful in helmet identification. To improve accident prevention measures, Siebert and Lin (2020) [5] suggested a methodology for helmet wear detection that is based on deep learning. Similarly, an intelligent surveillance system was used to investigate helmet use by Yogameena et al. (2019) [6]. Earlier studies demonstrated machine vision techniques for helmet identification in real-time (Waranusast et al., 2013; Dahiya et al., 2016). A more recent study by Shine and Jiji (2020) [13] compared CNN-based models to those using hand-engineered features, highlighting the superior accuracy of CNN. Trends in helmet use were investigated in naturalistic observational studies, which provide light on transportation-related behavioral patterns (Siebert et al., 2019; Ledesma et al., 2015; Siebert et al., 2019).

PROPOSED MODEL

Here, we take a look at the design specifications of the proposed Pairing Net + Light Weight Deep Sort Fast Yolo Rec Architecture. It's a system that can identify and punish traffic violations such as multiple vehicle racking, overspeeding, overloading, helmetless driving, frequent lane changes, fake numbers, and non-recognized license plate usage based on the video data collected from the government sensor network's base station. The structure looks like this:

ISSN:2454-9940 www.ijsem.org
Vol 20, Issuse.2 April 2026

3.1. Yolo Rec Architecture for Fast Video Processing
The Yolo Rec Architecture is used to handle video captured from government sensor network base stations or from benchmark repositories' coco datasets. The video that has been acquired is converted into picture frames. In order to generate multi-scale feature maps and extract features from images, each frame is sent to a backbone network. While the head model creates the object's bounding box, the neck component aggregates the generated multiscale feature map to maintain the essential hierarchical features. DenseNet121 and regulatory effectiveness make up the 3.1.1. backbone. In order to handle the picture frame of the sensor video with 1024*1024 receptive fields, DenseNet121, a convolutional neural network of 121 CNN layers, was developed by Boonsirisumpun et al. (2018) [12] and Vishnu et al. With the model's learning rate and epoch value defined, DenseNet processes the picture frame over many layers of the model, serving as the backbone for Yolo based object identification tasks [8]. Activation, softmax, and loss functions in the fully connected layer are used by the subsequent network to categorize the features of the objects that have been retrieved with various class labels. The suggested pairing net + lightweight deep sort fast yolo rec architecture for vehicle recognition and tracking is shown in Figure 1.

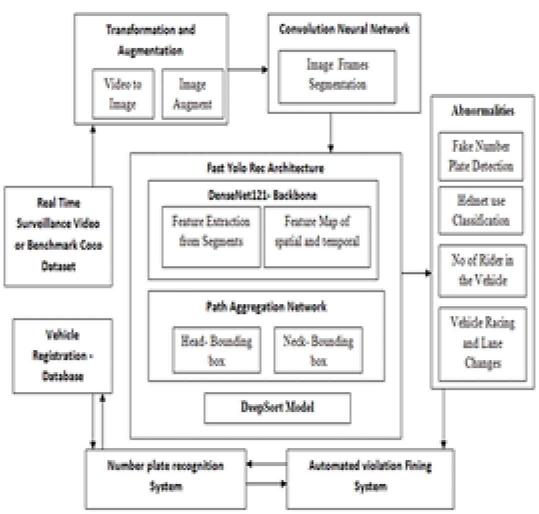

Figure 1: Proposed Architecture

In order to represent the areas of interest as picture segments, the DenseNet's convolution layer employs a filter to extract them from the picture frame. separate the areas of the picture if the standard deviation of the pixel intensity of g(x1,y1) is greater than g(x2,y2) Segment S is defined as the set of all picture segments where s1 and s2 are defined according to the pixel intensity. The multiscale feature is extracted from the segmented portions of the picture by further processing them using the kernel function and stride value. A multiscale feature map represents the low-level features, which are the multiscale characteristics of each divided area [9]. Feature map at the lowest level FMLm = (MSLfi,wi)D A segment window wi's multiscale low-level feature is denoted as MSLfi. Down Sampling Layer—Max Pooling Layer In order to downsample the picture segments' multiscale features, a max pooling layer is used. It takes each segment and uses its high-level properties to determine what each section is diagrammed and shown as a high-level feature map with many scales. Max pooled features are a kind of high-level multi-scale feature. The High level Feature map FMHM = (MSHfi,wi)N represents the feature map of each segment's high-level multiscale variables. The multiscale high level feature of the provided segment window wi is denoted as MSHfi. If In order to process the multiscale features, the Fully Connected layer employs the activation function, softmax function, and loss function. In order to classify the features of objects extracted with different class labels along the various operations, such as feature map augmentation, feature map regularization, and feature map smoothing, the activation function converts the multiscale features into linear form. Then, the linear features are fed into the softmax function [13]. The infractions and anomalies associated with each vehicle type are represented by their class designation.

Dense Net also aggregates the important hierarchical properties using the Cross stage Partial (CSP) Connection Block, Residual Block, and Dark Block [10]. The Dense Connected feature DC= { FML, FMH } represents the low-level and high-level object features of each picture segment. Class 3.1 violations include vehicle racing, lane changes, excessive speeding, and the use of fake number plates and helmets. Dense Connected Feature Map is used for this purpose.2. An auxiliary information-processing Path Aggregation Network called a Neck Path Aggregation Network may be used to identify objects of varied sizes by processing densely coupled multiscale properties. In doing so, it converts the multiscale characteristic into a spatial and pyramidal structure. The object mask, together with its bounding box and object scores, is then represented using the anchor box prediction technique. When it

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN:2454-9940 www.ijsem.org
Vol 20, Issuse.2 April 2026

comes to effectively localizing characteristics while reducing the difficulty of processing them, further route aggregation networks are very competent [11]. 3.1.3 Pairing Net PairingNet is a pair-searching and -matching network that is applied to the enormous bounding boxes of the various frames. It uses a graph convolution network as its foundation to identify items with matching textures and contours.

The next step for a pair-searching and matching network is to use contrastive learning to generalize item sizes across frames efficiently [12] 3.1.4. Categorization of Objects—In order to classify objects with bounding boxes, Head Fast yolo Rec-Head is used [14]. The vehicle is categorized using the bounding box, which is based on width and height. The position changes of the vehicle are shown using the geographical coordinates of the photos, and the speed of the vehicle is determined by this. Commuters may benefit from analytics solutions, such as real-time insights on organized traffic data of their favorite locations, as it forecasts the object's score to indicate the violation and initiates the automated fining system. Deepsort: Tracking Objects Using deep sort techniques, we can detect vehicles with fraudulent or unrecognized license plates, those traveling at excessive speeds, and vehicles of varying sizes. We can then divide these vehicles into subcategories based on factors such as the number of riders in the vehicle, the frequency with which the vehicle changes lanes, and the severity of accidents involving these vehicles. Step 1: Coordinated and Integrated Multiple Object Recognition Coco video dataset is used as input. The following are some of the main outputs: detection of fake and non-recognized number plates, detection of vehicles over speeding and accidents, classification of helmet use, and classification of the number of riders.

Process ()

Data Transform()

Data Format= Video to Image Converter (Input Sensor data)

Augmented Image frames =Augment(Data format)

Image Segmentation ()

Convolution Neural Network(Augmented Image frames)

Image segments = {S1,S2...Sn}

Fast Yolo Rec ()

Backbone -DenseNet121()

Convolution Layer (Kernel Function , No of Stride)

Low Level Multi Scale feature of the Image = Filter (Segment n)

Low level Multi Scale Feature Map = Map(Multiscale feature of each segment)

Max pooling layer (Kernel Function , No of Stride)

High Level Multi Scale feature of the Image = Filter (Segment n)

High level Multi Scale Feature Map = Map(Multiscale feature of each segment)

Dense Connected Layer ()

Activation Function () =ReLU(High level Multi Scale Feature Map| Low level Multi Scale Feature Map)

Softmax Function - Naive ayes Classifier (linear feature map of Low level and High Level Multiscale Feature)

Dense Connected Feature Map

PANet()_Neck

Transform ()

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN:2454-9940 www.ijsem.org
Vol 20, Issuse.2 April 2026

Pyramid Structure = Transform(dense connected multiscale features)

Spatial Structure = Transform (dense connected multiscale features) Pyramid aggregation()

Bounding Box for Structural features

Spatial Pyramid aggregation()

Bounding box for Spatial features

PairingNet()

Feature Searching (Graph Convolution Network)

Graph Transform(Structural and Spatial features)

Convolution layer()

Extract the similar feature in different image frames

Map the extracted similar features with same size

Contrastive Learning ()

Map the extracted similar feature with different size

Object Classification ()_Head

Classify Vehicle Type (Bounding Box of the object with structural features)

Vehicle type = {Two Wheeler, Car, Bus }

Compute Object Score ()

Bounding Box(x,y,w,h)

Coherence of bounding box with respect to the Vehicle spatial Coordinate changes

Classify Vehicle Speed (Bounding Box of the object with Spatial features)

Vehicle Speed = {Mild, Moderate, High }

EXPERIMENTAL RESULTS

By monitoring traffic in real-time, we can test out our present method of integrated object detection and automated fining. The current Pairing Net + Light Weight Deep Sort Fast Yolo Rec Architecture is tested using various performance metrics, including recall, precision, and Intersection of Union. The goal is to compare the model's detection efficiency and accuracy with that of traditional intelligent transportation methods implemented in the Python framework. The videos used for testing can be either obtained from the government's sensor network or an annotated benchmark dataset [10]. A video frame is used to train the model, which then uses the annotation process to locate the bounding boxes of various vehicle categories.

Table 2: Performance Evaluation

Technique	Precision	Recall	Prediction Accuracy	Prediction Efficiency	IOU
Pairing Net+ Fast Yolo Rec+ Deep Sort-proposed	99.68	98.1	99.75	99	0.09
Fast Yolo Rec-Proposed	99.28	97.8	99.18	99	0.07
Yolo V4 – Existing	98.32	97.14	98.25	98	0.05

Incorporating bounding boxes into the prediction model[15] to highlight items in relation to over speed, fake number plate, lane shifts, and helmet usage detection, the pairing of Net with Lightweight Deep Sort Fast Yolo Rec Architecture improves performance. Figure 2 and Table 2 show the calculated model detection accuracy.

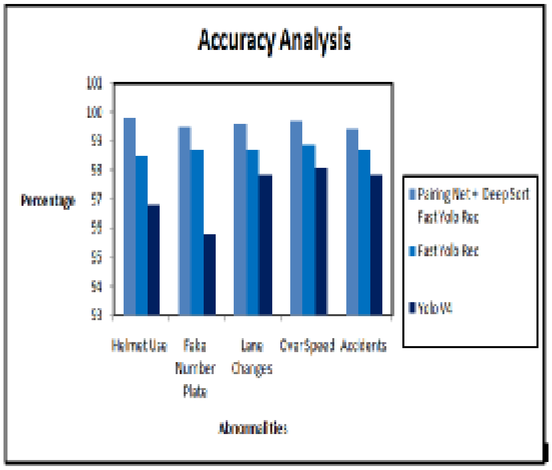

Figure 2 : Detection Accuracy

As shown in Figure 3, the Analysis Object Detection efficiency is determined by the Inter-Object Object (IOU) metric, which measures the degree of overlap between the bounding boxes.

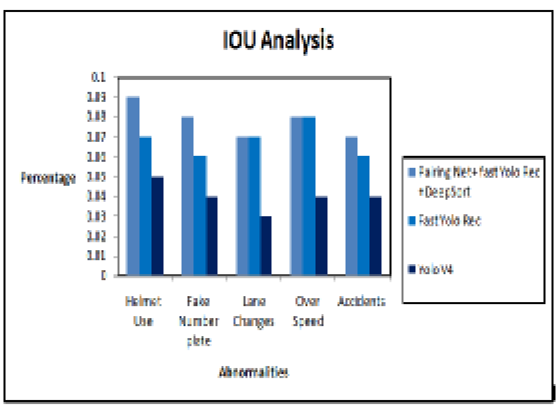

Figure 3: IOU Analysis

Due to the improved detection accuracy achieved by the new PairingNet+ Fast Yolo Rec +Deepsort architecture compared to the traditional yolo-based method, the current architecture classifies helmet usage, overspeeding, accidents, phony number plates, and lane changes as unusual or typical. The purpose of this system is to automatically generate fine tickets for traffic violations (such as speeding, helmet use, accidents, and fake number plates) and send them to the owners of the vehicles involved. In the event that a falsified plate is detected, the system will notify the local police station and the original owner of the malpractice. The results of the various object identification tasks utilizing fast yolo rec are shown in Figure 4.

Figure 3: Prediction Output of the Fast Yolo Rec model against Fake Number Plate Usage V.

CONCLUSION

Using Pairing Net + Light Weight Deep Sort Fast Yolo Rec Architecture, an automated fining system is developed and deployed in this article to detect traffic violations such as helmet use, over speeding, accidents, lane changes, and fake number plate recognition. This model's usage of a softmax layer of a convolutional neural network to identify abuse and an automated method to issue fine tickets for violations are two ways it helps to reduce traffic law violations. In order to identify violations and anomalies in traffic data from various vehicles, the model gathers and processes data from government agency sensor networks or extracts it from the benchmark coco dataset. In particular, the most recent model makes use of the following components: the DenseNet model serves as the model's backbone for segmentation; the Path aggregation Network to Neck model aggregates features; the head model recognizes objects; the pairing net compares two images in different frames; and the deep sort model tracks objects and the head model recognizes them. The results of the experiments show that the model outperforms the traditional designs in terms of accuracy.

REFERENCES

[1]. Y. Lv, Y. Duan, W. Kang, Z. Li, and F.-Y. Wang, ''Traffic flow prediction with big data: A deep learning approach,'' IEEE Trans. Intell. Transp. Syst., vol. 16, no. 2, pp. 865–873, Apr. 2015.

[2]. J. Wu, Z. Liu, J. Li, C. Gu, M. Si, and F. Tan, ''An algorithm for automatic vehicle speed detection using video camera,'' in Proc. 4th Int. Conf. Comput. Sci. Edu., Jul. 2009, pp. 193–196.

[3]. Y. Artan, O. Bulan, R. P. Loce, and P. Paul, ''Driver cell phone usage detection from HOV/HOT NIR images,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops, Jun. 2014, pp. 225–230.

[4]. Jyothis, Siva, Anand S. Nair, Kirandas VR, and Divya Visakh. "Developing a SmartRail Security System with YOLO and OpenCV." Journal of Ubiquitous Computing and Communication Technologies 6, no. 1 (2024): 28-38.

[5]. F. W. Siebert and H. Lin, ''Detecting motorcycle helmet use with deep learning,'' Accident Anal. Prevention, vol. 134, Jan. 2020, Art. no. 105319.

[6]. B. Yogameena, K. Menaka, and S. Saravana Perumaal, ''Deep learningbased helmet wear analysis of a motorcycle rider for intelligent surveillance system,'' IET Intell. Transp. Syst., vol. 13, no. 7, pp. 1190–1198, Jul. 2019.

[7]. F. W. Siebert, D. Albers, U. Aung Naing, P. Perego, and S. Chamaiparn, ''Patterns of motorcycle helmet use–A naturalistic observation study in Myanmar,'' Accident Anal. Prevention, vol. 124, pp. 146–150, May 2019.

[8]. R. D. Ledesma, S. S. López, J. Tosi, and F. M. Poó, ''Motorcycle helmet use in mar del plata, argentina: Prevalence and associated factors,'' Int. J. Injury Control Saf. Promotion, vol. 22, no. 2, pp. 172–176, Apr. 2015.

[9]. R. Waranusast, N. Bundon, V. Timtong, C. Tangnoi, and P. Pattanathaburt, ''Machine vision techniques for motorcycle safety helmet detection,'' in Proc. 28th Int. Conf. Image Vis. Comput. New Zealand (IVCNZ), Nov. 2013, pp. 35–40.

[10]. K. Dahiya, D. Singh, and C. K. Mohan, ''Automatic detection of bike-riders without helmet using surveillance videos in real-time,'' in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Jul. 2016, pp. 3046–3051.

[11]. C. Vishnu, D. Singh, C. K. Mohan, and S. Babu, ''Detection of motorcyclists without helmet in videos using convolutional neural network,'' in Proc. Int. Joint Conf. Neural Netw. (IJCNN), May 2017, pp. 3036–3041.

[12]. N. Boonsirisumpun, W. Puarungroj, and P. Wairotchanaphuttha, ''Automatic detector for bikers with no helmet using deep learning,'' in Proc. 22nd Int. Comput. Sci. Eng. Conf. (ICSEC), Nov. 2018, pp. 1–4.

[13]. L. Shine and C. V. Jiji, ''Automated detection of helmet on motorcyclists from traffic surveillance videos: A comparative analysis using hand-crafted features and CNN,'' Multimedia Tools Appl., vol. 79, pp. 14179–14199, Feb. 2020

[14]. H. Yang, L. Du, G. Zhang, and T. Ma, ''A traffic flow dependency and dynamics based deep learning aided approach for network-wide traffic speed propagation prediction,'' Transp. Res. B, Methodol., vol. 167,pp. 99–117, Jan. 2023.

[15]. Bharti, P. Redhu, and K. Kumar, ''Short-term traffic flow prediction based on optimized deep learning neural network: PSO-Bi-LSTM,'' Phys. A, Stat.Mech. Appl., vol. 625, Sep. 2023.