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Virtual Traffic Police

O Josna, Harshitha V, Karuna M, Dhanushree S

Assistant Professor, Department of Computer Science & Engineering, Rajarajeswari College of Engineering, Bengaluru, Karnataka, India

UG Student, Department of Computer Science & Engineering, Rajarajeswari College of Engineering, Bengaluru, Karnataka, India

ABSTRACT: This article explores the enhancement of traffic law enforcement through utilization of augmented reality and deep learning techniques, specifically centering on the implementation of YOLOv3 for detecting violations like signal jumping, speeding, and traffic volume monitoring. The goal is to reduce traffic offenses and enhance road safety by accurately identifying and penalizing offenders. It covers the fundamentals of traffic violation detection, including image representation and the YOLOv3 algorithm, along with concrete instructions for architecture and implementation. The article emphasizes the significance of computer vision technology in overseeing and enforcing traffic regulations, showcasing its ability to detect multiple violations concurrently with great accuracy. Simulation and analysis results illustrate the effectiveness of the architecture in identifying issues such as signal irregularities, offering comprehensive insights into the detection procedure and resulting data. In summary, this piece underscores how AI and deep learning can advance traffic management and promote road safety.

KEYWORDS: Convolutional neural networks, traffic violation, YOLOV3.

I. INTRODUCTION

As the vehicles increases on roads the calming of the traffic also increases. These systems are essential for calming the traffic in identifying and fining people who do not follow the instructions. In previous years, traffic violations were typically detected by police stationed at intersections, nonetheless, this step has been shown inefficient and time-consuming, especially during periods of heavy traffic. To address these challenges, the hypothesis of traffic analysis and enforcement using computer vision technology has emerged. Computer vision involves using intelligent algorithms to interpret visual data from images and videos. By employing computer vision algorithms, traffic violation detection systems can analyze video feeds from road cameras to identify and sanction drivers for infractions such as speeding or illegal crossing. Computer vision offers scalability and cost-effectiveness compared to traditional methods. These systems can work without any break with less man oversight, reducing operational expenses and improving efficiency. Moreover, this is deployed in various locations such as urban areas and highways, providing comprehensive surveillance and enforcement services. In summary, using manmade thinking tech for traffic management purposes leverages artificial intelligence and image processing to efficiently address traffic- related challenges and enhance overall road safety. The adoption of manmade thinking can completely upgrade the traffic management and upgrade traffic calming for all people.

II. LITERATURE SURVEY

G. Sasikala et al. [3] introduced a system based on RF transmitter and receiver to enhance helmet features and provide additional protection during accidents. However, this approach may lead to an increase in helmet costs and does not provide a solution to mandate helmet usage for all riders and non-riders.. Narong Boonsirisumpun et al. [4] proposed a system using a CNN to classify helmets and motorcycles. However, CNN's performance is limited by training samples, making it prone to false recognition, especially if individuals wear different types of helmets or cover their faces. Liang-Bi Chen et al. [5] suggested a system employing IR sensors in an intelligent helmet for detecting nearby heavy vehicles and alerting riders to potential dangers. This system uses a helmet-mounted camera to identify approaching heavy vehicles. Mario Andres Varon Forero et al. [6] developed a project using CNN and background subtraction to highlight

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riders wearing helmets. The system classifies helmets using support vector machines based on training data, achieving decent accuracy but facing challenges in real-world scenarios such as obscured faces or passengers without helmets. Rohith C A et al. [7] proposed a CNN-based system capable of detecting two-wheelers with and without helmets. However, CNN's limitations with training data mean it may struggle to handle diverse situations effectively. Detecting multiple helmets and distinguishing heads alongside motorcycles poses significant challenges.

III. PROBLEM STATEMENT

The objective of this project is to enhance cyclist safety, particularly addressing the issue of non-compliance with helmet regulations despite their mandatory status. Bengaluru boasts approximately 5 million two-wheeler riders, making it a top cities for two-wheeler usage. Unfortunately, the city experiences around 500-600 accidents annually, resulting in 300-400 fatalities. The percentage of road accidents has notably increased in recent years, underscoring the critical need for measures to reduce these fatalities. Some telecom operators have adopted a device equipped with sensors to monitor traffic distribution and track employees, cross-referencing the data with manual entries. However, this system is expensive, complex, and demands extensive maintenance. Our research seeks to seek different process that are more cost- effective and efficient to replace this costly process.

IV. PROPOSED SYSTEM

This part explains recommendations for addressing the problem of helmetless cyclists through a structured two-stage approach. In the initial stage, cyclists are captured on video using surveillance systems or cameras deployed in strategic locations. In the subsequent stage, a series of checks are performed on the detected individuals, including analyzing the presence of a passenger's head, verifying their driver's license, and checking if they are wearing a helmet or not. To amplify measurement and minimize false predictions, a method of aggregating consecutive results is employed, leading to a final decision or prediction regarding helmet usage. The block diagram accompanying this approach illustrates various critical steps within the framework. These steps encompass processes like background subtraction, object detection, and classification, all of which are critical for correctly identifying helmetless individuals. Cost considerations are integral to this process, ensuring that the implementation remains economically viable. Techniques such as background subtraction are applied to grayscale images to isolate abnormal or static objects, facilitating subsequent analysis and decision-making. In the upcoming discussions, we will delve deeper into the modeling aspects of this approach, exploring the methodologies employed in each stage of the framework. By adopting this comprehensive strategy, we aim to effectively address the challenge of ensuring helmet compliance among cyclists while optimizing resources and technology for maximum impact on road safety.

V. IMPLEMENTATION

The implementation of a license plate recognition (LPR) system involves several key components and processes, particularly focused on optical character recognition (OCR) for accurate plate identification.

1. METHODOLOGY

1. Image Acquisition: The first step involves capturing images containing vehicles and their license plates using cameras positioned strategically, such as at toll booths, parking lots, or intersections. Pre-processing: Raw images captured by the cameras undergo pre-processing to enhance quality and facilitate effective OCR. This includes tasks like noise reduction, image resizing, and contrast adjustment.
2. License Plate Localization: The system uses algorithms to detect and localize license plates within the pre-processed images. Techniques such as edge detection, morphological operations, or machine learning-based detection of the object used for accurate plate extraction. Character Segmentation: Once the license plate region is identified, individual characters on the plate has to be segmented for OCR. This step involves isolating each character from the plate image, considering variations in plate design and character spacing.
3. Optical Character Recognition (OCR): OCR algorithms are applied to the segmented characters to recognize and convert them into machine-readable text. Machine learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are commonly used for robust character recognition.

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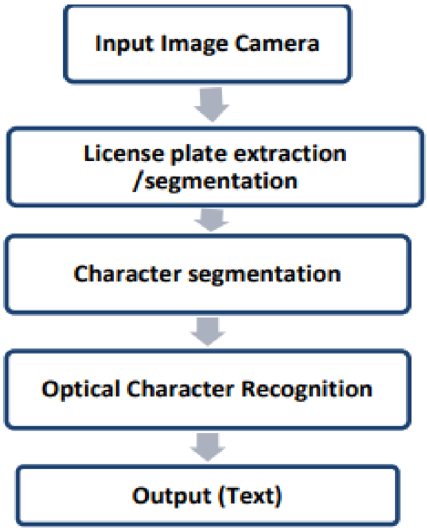
4. Post-processing and Error Correction: The OCR output undergoes post-processing to correct errors and improve accuracy. Techniques like dictionary-based correction, pattern matching, or confidence score thresholds used to filter the recognized text.
5. License Plate Verification: Finally, the recognized plate number is verified against databases to perform tasks such as vehicle tracking, automated toll collection, or law enforcement activities. The calculation of system performance typically involves characteristics like precision, and processing speed. These metrics assess the system's ability to correctly identify license plate numbers in other situations, along with other lighting, weather, and vehicle speeds.



2. ALGORITHM

CONVOLUTIONAL NEURAL NETWORK:

CNN are being utilized across different fields which has NLP, speech recognition, and pattern recognition. A CNN can be of feed-forward, multilayer neural network, akin to an artificial neural network (ANN), which processes input data through a series of computational layers. The architecture of a CNN is characterized by a sequence of distinct layers, each serving a specific function within the network.

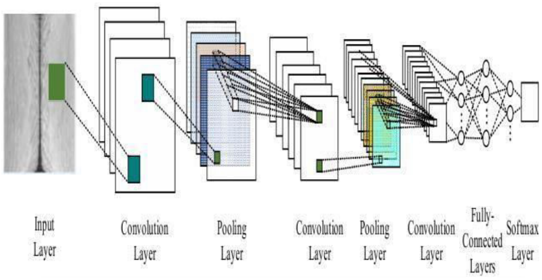


Figure 5.2 illustrates the architecture of a CNN. Unlike in artificial neural networks (ANNs), each neuron in a CNN receives input from a localized region that matches the size of the convolutional kernel. This approach ensures that the trained CNN can effectively extract meaningful features, which play a crucial role in enhancing system performance.

THE CNN ARCHITECTURE COMPRISES SEVERAL KEY LAYERS:

Convolutional Layer: This layer contains parameters represented by a set of learnable kernels that are optimized through the back propagation algorithm. Each kernel scans across the input data, producing a feature map which convolves with the input. The quantum of these feature maps corresponds to the quantum of kernels utilized in the

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layer. The ReLU activation function introduces nonlinearity into the network. Notably, using ReLU is essential for learning in CNNs, providing advantages over different functions like sigmoid or tanh. Furthermore, output from this layer can be significantly faster to compute compared to other operations, without compromising accuracy. x and y are the ith input activation map and the jth output map. b is the deviation of the jth output map and * indicates the convolution. j is the convolution kernel between the ith input map and the jth output map. ReLU activation function is used to add nonlinearity to the network.

$$y^{j(r)} = \max\left(0, b^{j(r)} + \sum_{i} k^{ij(r)} * x^{i(r)}\right)$$

Maximum Pooling Layer: The primary role of the pooling layer is to reduce the spatial dimensions (size) of the input volume acquired from the convolutional layer. When data progresses through successive layers, this reduction in size helps manage computational complexity while preserving essential features crucial for pattern recognition. The maximum pooling operation within this layer retains the highest quantum in each region, effectively downsampling the input. Other types of pooling layers include average pooling and min pooling, but maximum pooling is widely used and well-known for its effectiveness in retaining important features during downsampling. Here, y represents the neuron in the ith output activation map that is computed over a non-overlapping local region of size (s x s) in the ith input map x.

$$y^{i}_{j,k} = \underbrace{max}_{0 \le m,n < s} \left(x^{i}_{js+m,ks+n}\right)$$

Fully Connected Layer: Following the convolutional layers or maximum pooling layers, the output is flattened and fed into more than one dense layers. In a fully connected layer, every neuron's o/p from the previous layer is connected to every neuron in the subsequent layer. This dense connectivity allows the network to learn complex patterns and relationships in the data, facilitating high-level feature representation and classification tasks.

$$y^{(l)}(j) = \varphi^{(l)}\left(\sum_{i=1}^{N^{(l-1)}} y^{(l-1)}(i).w^{(l)}(i,j) + b^{(l)}(j)\right)$$

Softmax Output Layer: As part of the overall system integration, a Softmax regression layer is employed for multi-class classification tasks. This layer uses the Softmax function to compute probabilities across multiple classes. Suppose there are K classes and n training samples. For each input fed into the Softmax classifier, the output is a K multidimensional vector is used to represent the probabilities of an input belonging to different classes. Each element in the vector corresponds to the likelihood of the input being associated with a specific class. This concept is commonly encountered in machine learning and statistical modeling, especially in tasks like classification and prediction.. The Softmax function ensures that the probabilities across all classes sum up to 1, enabling effective classification of input data into multiple categories. This layer is pivotal for making predictions and assigning class labels depends on the highest probability value within the output vector.

$$\mathrm{P}(y_i = m|x_i; W) = a_i = \frac{e^{w_i^T x_i}}{\sum_{j=1}^{K} e^{w_j^T x_j}}$$
$$, m \in (1,2, \ldots, K)$$

Where W=(w1,w2,….,wk) are the parameters to be learned by the backpropagation algorithm. The cross- entropy loss can be used as the cost function for the Softmax classifier and can be detected as follows:

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$$J(W) = -\sum_{i=1}^{N}\sum_{j=1}^{K} y_{ji} log\left(\frac{e^{w_j^T x_i}}{\sum_{m=1}^{K} e^{w_m^T x_i}}\right)$$

S N - the quantum of data points in the training set. A gradient descent method is then used to solve for the minimum of J(W) as follows:

$$\nabla_W J(W) = \sum_{i=1}^{N} x_i (a_i - y_i)^T$$

Finally, the parameters are updated as follows:

$$W^{new} = W^{old} - \eta \nabla_W J(W)$$

YOLO algorithm:
YOLO (You Only Look Once) is a widely used real-time detection of the object that varies from traditional methods by employing a one network of neural to perform object classification and localization simultaneously within an image. Applications of YOLO include surveillance, driverless cars, robotics, and more.

Fig: Input Image

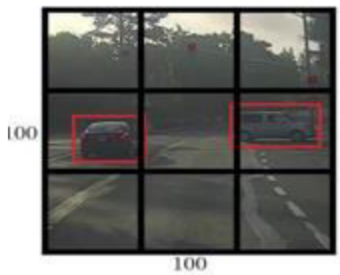

Fig: Grid Frame

OCR Algorithm:
OCR is an algorithm used to extract text content from images, enabling machines to interpret and process text data.
It works by analyzing pixels in an image and comparing them with stored data to recognize characters. Unrecognized characters are marked as "unknown."
OCR uses machine learning techniques to determine alongwith classifying groups of pixels representing text patterns, extracting features through training processes.

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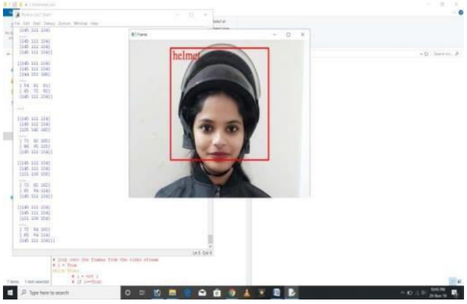
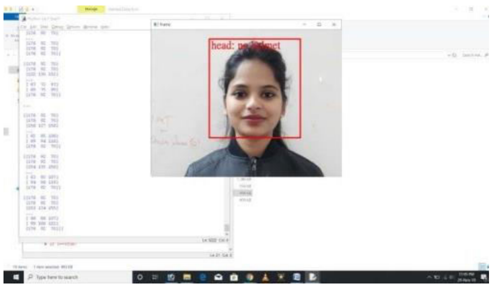
VI. RESULTS AND DISCUSSIONS

The project evaluates the working of YOLO and OCR through various scenarios, including frames depicting individuals with helmets, without helmets, different types of heads, and multiple heads or helmets.

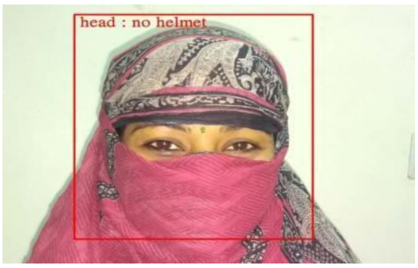


Giant. 6.1. Helmet detection



Giant. 6.2. Head detection without a helmet

Giant. 6.1 and 6.2 are helmet detection and non-helmet head detection.



Giant. 6.3. Head detection without a helmet

Giant. 6.3 shows a woman without a helmet and her face is covered by a weft, which is accurately detected by the system. Here the violation is recognized by the system.

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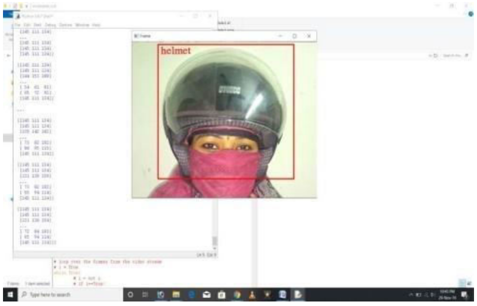
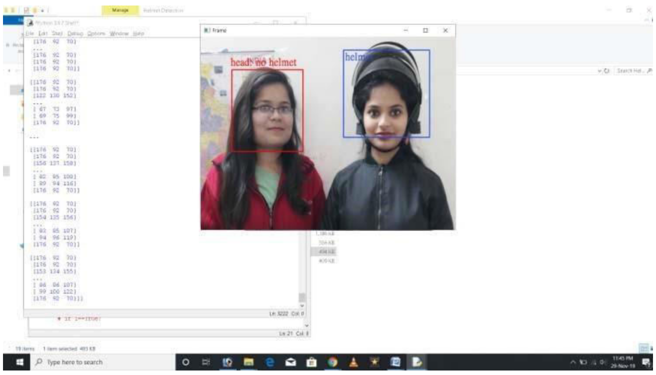


Giant. 6.4. Helmet Detection Even Face Covered

Giant 6.4 demonstrates the system's ability to detect helmets even when faces are covered. In cases which consists a single person on the given area and the system detects a helmet instead of a head, it suggests that no intrusion is detected. However, if multiple people are present in the motorcycle frame and the system detects a helmet on one individual but not on another, such as a passenger being helmetless while the rider wears a helmet, this represents a violation of safety standards.



Giant. 6.5. Multi-person head and helmet detection.

The project is evaluated using frames containing multiple individuals, both with and without helmets. The system demonstrates accurate and reliable recognition of these scenarios.

VII. CONCLUSION

The proposed framework serves as a substitute for police officers in monitoring traffic. It utilizes traffic surveillance techniques focusing on motion detection, license plate extraction, and feature recognition. When a violation occurs, the framework captures an image of the incident, extracts the license plate information, and verifies the tag characters. A traffic violation notice is then issued, and vehicle owners are notified of the specific violation type and the corresponding fine amount.

VIII. FUTURE SCOPE

Advancements of the model pave the roadmap to the future works and evolution in the realm of traffic control robotics. Future plans include refining component designs for enhanced precision and developing more comprehensive strategies. Additionally, there is potential to design intelligent systems, such as a smart bike, that can detect and address violations like ignoring helmet usage. The framework may also be expanded to accurately detect and record the

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quantum of traffic offenders within a specific area.

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