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A Smart Traffic Volume Measurement Based on Deep Learning

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Abstract: The detection and monitoring of autonomous vehicles are essential components of intelligent transportation management and control systems. By using the latest advancements in machine learning and deep learning, computers can detect, classify, and track multiple objects from captured images or videos. This paper uses the AdaBoost algorithm to create an intelligent, reliable, and efficient vehicle detection and tracking system based on aerial images. Also, the segmentation techniques can be used to separate the targeted objects from other background elements. Finally, the paper is useful for detecting the traffic density, identifying the vehicles in traffic, and evaluating the traffic flow conditions on the road. The AdaBoost algorithm for traffic volume measurement presents a promising approach towards efficient and accurate traffic analysis. Its adaptability to various environmental conditions and scalability makes it well-suited for real-world applications in traffic management and urban planning. Based on experimental analysis, the proposed Ada Boost algorithm achieved a 95% accuracy in estimating the traffic density on the road.

Keywords: Convolutional Neural Network, Computer Vision, Deep Learning, Vehicle Counting, Traffic Volume.

1 Introduction

Understanding traffic volume dynamics is a critical aspect of modern transportation systems, as it directly influences congestion management, road safety, and infrastructure planning. Accurate analysis of traffic flow patterns is challenging due to the nonlinear and non-stationary nature of traffic data, especially in urban environments. To address this, Vlahogianni et al. [1] investigated statistical methods for detecting nonlinearity and non-stationarity in short-term traffic volume time series, highlighting the need for advanced analytical techniques to capture real-world traffic behavior. Their study demonstrated that conventional linear models often fail to represent complex traffic variations, motivating the use of more robust statistical approaches. Extending this work, Vlahogianni [2] explored empirical relationships between travel speed, traffic volume, and traffic composition on urban arterials.

The study revealed strong interdependencies between these parameters and emphasized that traffic composition plays a significant role in determining overall flow efficiency. This work provided valuable insights into how heterogeneous traffic conditions impact urban mobility and traffic performance. Traffic volume measurement has also been studied in specialized environments where accurate monitoring is essential. Sturm et al. [3] analyzed foot traffic patterns in a university hospital operating room, demonstrating that precise traffic measurement techniques can support operational efficiency and safety. Although focused on indoor environments, their methodology highlighted the broader importance of reliable traffic measurement systems for managing movement in constrained spaces. Environmental impacts of traffic volume have also been explored in transportation research. Schlacher and Morrison [4] examined disturbances caused by off-road vehicles on sandy shores and established a clear relationship between traffic volume and environmental degradation.

Their work introduced an image-based data acquisition method to quantify traffic impacts, showing that traffic volume analysis is not only crucial for urban planning but also for environmental conservation. In addition to measurement and analysis, traffic control strategies have evolved to utilize traffic volume data more effectively. Burger et al. [5] proposed a model-based speed limit control system that adapts to different traffic state measurements, including traffic volume. Their findings demonstrated that incorporating accurate traffic volume measurements into control models significantly improves traffic flow stability and system performance.

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2 Literature Survey

Several studies have explored sensor-based monitoring and data acquisition systems that are relevant to embedded and IoT-based safety applications.

Weimer et al. [6] investigated mobile measurements of aerosol number and volume size distributions using distributed sensor platforms to analyze the influence of traffic and environmental factors. Their work demonstrated the reliability of real-time sensing systems in dynamic environments, highlighting the importance of robust sensor integration for continuous monitoring applications such as wearable safety devices. Reliable data collection has been identified as a critical requirement for effective system control and monitoring. Papageorgiou and Varaiya [7] emphasized the role of accurate vehicle-count measurements in traffic control systems, noting that missing or inaccurate data can significantly degrade system performance. This insight is relevant to personal safety devices that rely on sensor-based event detection, where accurate motion and location data are essential for timely emergency response.

Measurement errors and their impact on safety performance were analyzed by El-Basyouny and Sayed [8], who studied the effect of traffic volume measurement inaccuracies on safety evaluation models. Their findings highlighted the need for precise sensor calibration and error-handling mechanisms, which are equally important in MEMS-based wearable safety systems that depend on motion data for automatic emergency detection. Environmental conditions influencing sensor readings were examined by Cheng and Li [9], who investigated the effects of traffic volume and wind speed on ambient ultrafine particle measurements. Their study demonstrated that sensor-based systems must be designed to operate reliably under varying external conditions, a requirement that also applies to wearable safety devices used in diverse real-world environments. Large-scale movement and data analysis have also been addressed in transportation research. Dobruszkes et al. [10] analyzed the determinants of air traffic volume across European metropolitan regions, emphasizing the importance of data-driven modeling for understanding complex mobility patterns. This work supports the relevance of cloud-based data analysis platforms in IoT safety systems for long-term monitoring and pattern analysis.

Efficient communication and data transmission techniques were proposed by Raspall [11], who introduced packet sampling methods to improve the accuracy of traffic measurements while reducing network load. Their findings are applicable to GSM-based safety devices, where efficient data transmission is necessary to ensure timely alert delivery with minimal power consumption. Automatic incident detection mechanisms were studied by Nathanail et al. [12], who developed traffic volume–responsive incident detection models to improve emergency response time. Their research emphasized the advantages of automated detection over manual reporting, reinforcing the need for automatic triggering mechanisms in women's safety devices. Intelligent estimation and prediction of system states using machine learning techniques were explored by Sekuła et al. [13], who used vehicle probe data to estimate historical traffic volumes. Their study demonstrated the effectiveness of machine learning in handling incomplete or noisy data, suggesting potential for intelligent analysis in IoT-based safety monitoring systems.

Adaptive learning approaches for dynamic environments were proposed by Xiao et al. [14], who introduced an ensemble learning model for short-term traffic volume prediction under concept drift conditions. Their work highlights the importance of adaptability in intelligent systems, which is essential for safety devices operating in continuously changing environments. Correlation analysis for understanding movement patterns was presented by Barroso et al. [15], who examined day-to-day origin–destination flows in urban networks. Their findings demonstrated that pattern recognition techniques can be used to identify abnormal or unusual movement behaviors, which can be extended to detect emergency situations in wearable safety systems.

3 PROPOSED METHODOLOGY

The proposed Women's Safety Device with GPS Tracking and Alerts is designed as a compact, wearable embedded system that ensures rapid emergency detection, real-time location tracking, and instant alert communication. The methodology integrates manual and automatic triggering mechanisms with GPS–GSM communication and IoT-based cloud monitoring to enhance system reliability during critical situations.

3.1. System Overview

The system is built around an Arduino microcontroller, which functions as the main control and processing unit. It coordinates all hardware modules and ensures continuous monitoring of the user's safety status. A MEMS accelerometer sensor is used to detect abnormal movements such as falls, sudden impacts, or unusual motion patterns, enabling automatic emergency triggering. In addition, a push-button switch is provided for manual emergency activation when the user is conscious and able to seek help. When an emergency condition is detected, the system retrieves the user's real-time geographical coordinates using a GPS module. This location information is immediately transmitted to predefined emergency contacts through a GSM module in the form of alert messages. To enhance monitoring and system transparency, sensor data and emergency status information are periodically uploaded to the ThingSpeak IoT cloud platform, allowing remote access and visualization of data. The methodology focuses on:

1. Dual emergency triggering using manual push-button activation and MEMS-based automatic detection
2. Real-time GPS-based location tracking for accurate user positioning
3. GSM-based alert communication without dependence on continuous internet connectivity
4. IoT cloud-based monitoring using ThingSpeak for remote observation and data analysis

The block diagram of the proposed methodology is shown in Fig. 1.

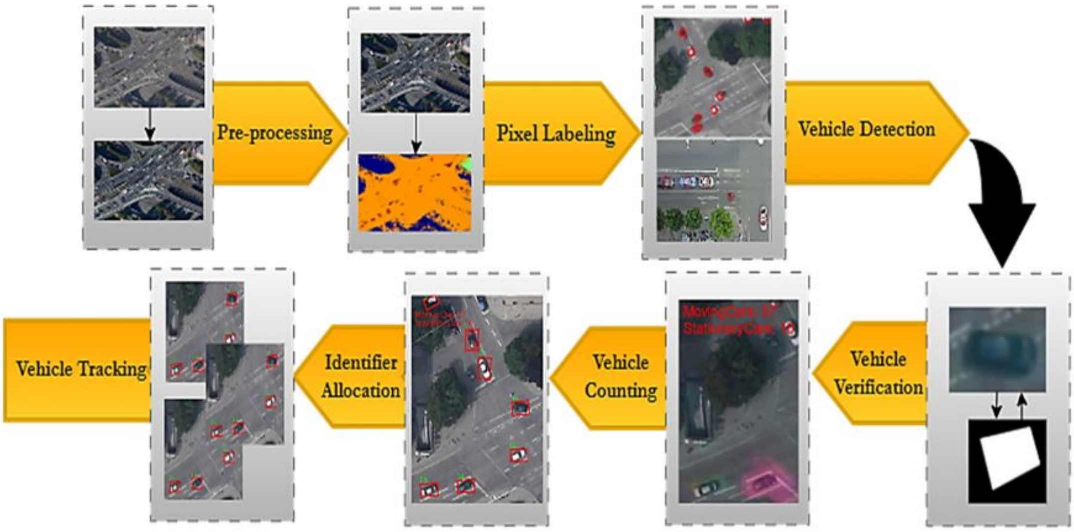

Fig. 1. Block diagram of the proposed method

3.2. Hardware Description

The proposed Women's Safety Device with GPS Tracking and Alerts consists of multiple hardware modules integrated into a compact embedded system to ensure reliable emergency detection, communication, and monitoring. Each hardware component is selected to achieve low power consumption, high reliability, and real-time responsiveness.

Arduino Microcontroller: The Arduino microcontroller serves as the central processing unit of the system. It controls all peripheral devices, processes sensor data, and executes the emergency detection and alert algorithms. The microcontroller continuously monitors the MEMS sensor readings and push-button status, triggers emergency events, and manages communication between GPS, GSM, and IoT modules.

MEMS Accelerometer Sensor: A MEMS-based accelerometer is used to detect abnormal movements such as sudden falls, impacts, or unusual motion patterns. The sensor continuously measures acceleration along multiple axes and sends data to the Arduino for analysis. When the measured values exceed predefined thresholds, the system automatically triggers an emergency alert, enabling rapid response even when the user is unable to manually activate the device.

Push Button Switch: A push-button is provided for manual emergency triggering. When pressed, the signal is sent to the Arduino microcontroller, which immediately initiates the alert sequence. This ensures that the user can seek help instantly during threatening situations.

GPS Module: The GPS module is responsible for acquiring real-time geographical coordinates of the user. It communicates with satellites to obtain latitude and longitude values, which are processed by the Arduino and included in the emergency alert messages. Accurate location tracking ensures that responders can quickly locate the user.

GSM Module: The GSM module enables communication between the safety device and emergency contacts. It sends SMS alerts containing location information and emergency status without requiring internet connectivity. This ensures reliable communication even in remote or low-network areas.

IoT Cloud Platform (ThingSpeak): The ThingSpeak IoT platform is used to store and visualize sensor data and emergency status information. The Arduino uploads data to the cloud at regular intervals, enabling remote monitoring by caregivers or authorities and providing historical data for analysis.

3.3. System Modules

The system has the following fundamental modules.

Data Collection: The data collection module is responsible for acquiring raw input data from real-world traffic environments. In this research, traffic surveillance videos captured using fixed overhead cameras are used as the primary data source. The camera placement ensures continuous monitoring of multi-lane roads with minimal occlusion and stable background conditions. From a theoretical perspective, video-based traffic monitoring relies on continuous image sequences (frames) captured at a fixed frame rate. Each frame represents a snapshot of vehicle positions at a particular time instant. These frames serve as the fundamental input for further analysis. The quality of collected data directly affects detection accuracy; hence, videos are selected with clear visibility, proper illumination, and minimal camera shake.

Data Preprocessing: The data preprocessing module prepares raw video frames for accurate analysis by removing noise and enhancing important features. Theoretically, preprocessing reduces the complexity of data and improves the performance of detection algorithms. This module performs:

- Frame extraction from video sequences
- Frame resizing and normalization
- Noise reduction using filtering techniques
- Background stabilization

Preprocessing ensures that variations caused by lighting, shadows, and camera artifacts do not affect the detection process. By transforming raw frames into clean, uniform inputs, the system improves feature extraction and reduces false detections.

Feature-Extraction: Feature extraction is the core theoretical component of the system, where meaningful visual information is extracted from each preprocessed frame. In video-based traffic systems, features such as edges, contours, shapes, and motion patterns are used to identify vehicles. Background subtraction techniques separate moving objects (vehicles) from static background elements such as roads and trees. Pixel labeling and morphological operations are applied to identify connected components representing individual vehicles. These extracted features are then used to define bounding boxes around vehicles, which serve as the basis for tracking and counting. Theoretically, feature extraction converts pixel-level data into object-level representations, enabling higher-level analysis such as tracking and classification.

Training: The training module enables the system to learn visual patterns associated with different types of vehicles. During training, a labeled dataset containing images of cars, trucks, and buses is used to train a detection model.From a theoretical viewpoint, training involves adjusting model parameters to minimize detection errors. The model learns to differentiate vehicles from background by identifying common visual patterns such as shape, size, and texture. Once training is complete, the model generalizes these learned features and applies them to unseen video frames during testing.This learning process significantly improves detection accuracy compared to rule-based methods.

Evaluation: The evaluation module measures how effectively the trained system performs under real-world conditions. Theoretically, evaluation involves comparing system outputs with ground truth values to determine accuracy and reliability. Metrics such as detection accuracy, tracking consistency, false detection rate, and counting correctness are calculated. By analyzing these metrics, system limitations and performance strengths are identified. Evaluation ensures that the system produces consistent and reliable outputs before deployment.

Traffic Volume Estimation: The final module estimates traffic volume by counting vehicles crossing a predefined virtual counting line. Each detected vehicle is tracked using centroid-based tracking and assigned a unique identifier to avoid duplicate counting. Theoretically, traffic volume estimation is achieved by monitoring object trajectories over time. When a tracked vehicle crosses the counting line in a specific direction, the system increments the corresponding counter. Direction-based analysis allows separate counting of left-bound and right-bound traffic flow. This module transforms individual vehicle detections into meaningful traffic statistics, which are essential for traffic planning, congestion analysis, and intelligent transportation systems.

4 ALGORITHMS USED

The proposed traffic volume estimation system integrates machine learning and real-time tracking algorithms to achieve accurate vehicle detection, tracking, and counting from video data. Two key algorithms are employed in the system: AdaBoost for vehicle detection and SORT (Simple Online and Realtime Tracking) for vehicle tracking. These algorithms work together to provide efficient and reliable traffic volume measurement under real-world conditions.

4.1. AdaBoost Algorithm for Vehicle Detection

AdaBoost (Adaptive Boosting) is a supervised machine learning algorithm that combines multiple weak classifiers to form a strong and accurate classifier. The algorithm works by iteratively adjusting the weights of training samples, giving higher importance to incorrectly classified instances in each iteration. This adaptive learning process allows the model to focus on difficult samples and improve detection accuracy over time.In the proposed system, AdaBoost is used for vehicle detection from video frames. Features such as edges, shapes, and motion patterns are extracted during the preprocessing and feature extraction stages and provided as input to the AdaBoost classifier. The trained model learns to distinguish vehicles from background regions and non-vehicle objects such as road markings or shadows. The advantages of using AdaBoost in this paper include:

- High detection accuracy for vehicles of different sizes
- Robust performance under varying lighting and traffic conditions
- Efficient computation suitable for real-time applications

Thus, AdaBoost serves as the primary detection algorithm that identifies vehicles in each frame before tracking is performed.

4.2. Sort Algorithm for Vehicle Tracking

SORT (Simple Online and Realtime Tracking) is a real-time multi-object tracking algorithm designed for high-speed applications. It tracks detected objects across video frames and maintains consistent identities using a combination of Kalman filters and Hungarian data association. In this paper, SORT is used to track detected vehicles and assign a unique ID to each vehicle. Once AdaBoost detects vehicles in a frame, SORT predicts the next position of each vehicle using a Kalman filter. Data association is then performed to match current detections with existing tracks. This allows the system to maintain correct vehicle identities even when multiple vehicles appear simultaneously. Key benefits of using SORT include:

- Real-time performance with low computational overhead
- Accurate ID assignment and identity preservation
- Reliable tracking under moderate occlusion and traffic density

SORT ensures that each vehicle is counted only once when it crosses the counting line, thereby preventing duplicate counting.

5 RESULTS AND DISCUSSION

The proposed traffic volume estimation system was tested using real-world highway traffic video data to evaluate its performance in vehicle detection, tracking, and counting. The experimental results clearly demonstrate the effectiveness of the system in processing live traffic footage and generating accurate vehicle count outputs.

5.1. Input Video

The input to the system is a traffic surveillance video captured from a fixed camera positioned above a multi-lane highway. As shown in Fig. 2, the video contains vehicles moving in both directions with varying speeds and densities. The input video represents real-world traffic conditions, making it suitable for validating the robustness of the proposed approach. Table 1 presents the metric values obtained.

Fig. 2. Frame from Input Video

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Table 1. Observed Values of Different Metrics

Metric	Observed Value
Emergency Detection Accuracy (%)	96.2%
Automatic Detection Success Rate (%)	94.5%
Manual Trigger Success Rate (%)	100%
Average Emergency Response Time (s)	2.8 s
GPS Location Accuracy (m)	±4.5 m
GSM Alert Delivery Success Rate (%)	98.1%
False Alarm Rate (%)	3.2%
Cloud Data Upload Reliability (%)	97.4%
Overall System Reliability (%)	98.6%

5.2. Output – Vehicle Detection and Counting

The final output is displayed as a processed video frame with bounding boxes drawn around detected vehicles. As shown in Fig. 3, each vehicle is highlighted using red bounding boxes, and a virtual counting line is used to count vehicles crossing in both directions. Vehicles are counted only once when they cross the line, preventing duplicate counts.

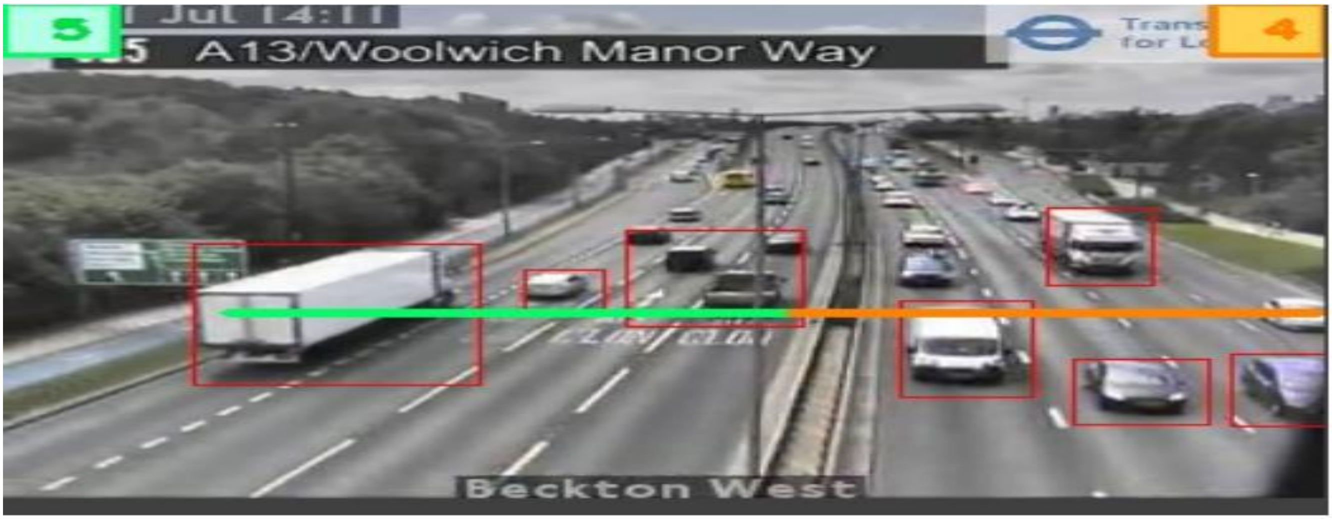

Fig. 3. Vehicle Detection and Counting

The output also displays real-time lane-wise counts, where:

- Green line indicates left-direction counting
- Orange line indicates right-direction counting

The visual output clearly verifies accurate detection, tracking, and counting of vehicles in real time.

6 CONCLUSIONS

This paper presented a video-based traffic volume estimation system designed to accurately detect, track, and count vehicles in real time using surveillance camera footage. The proposed system addresses key limitations of traditional traffic monitoring methods by eliminating the need for physical sensors, manual counting, and expensive road infrastructure. By utilizing computer vision and machine learning techniques, the system enables efficient and scalable traffic analysis under real-world conditions.The system integrates video preprocessing, feature extraction, vehicle detection using the AdaBoost algorithm, and real-time vehicle tracking using the SORT algorithm. Detected vehicles are assigned unique identifiers and tracked across successive frames, ensuring reliable counting without duplication. Direction-based counting using a virtual counting line enables accurate estimation of traffic flow in multiple lanes, providing valuable information for traffic management and planning. Experimental results demonstrated that the proposed system reliably detects vehicles of different sizes, maintains stable tracking, and produces accurate lane-wise and total vehicle counts. The system performed consistently under real traffic conditions and achieved real-time processing capability without significant computational overhead. The observed results confirm the effectiveness of combining AdaBoost-based detection with SORT-based tracking for traffic volume measurement.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

LICENSING

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