IOT Based Speed Control Monitoring and Accident Avoidance Using AI Traffic Sign Detection

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***Abstract* - The escalating number of road accidents worldwide, driven by human errors such as driver fatigue, over speeding, and failure to adhere to traffic regulations, underscores the urgent need for advanced safety mechanisms in transportation. This research presents a pioneering system that integrates the Internet of Things (IoT) with artificial intelligence (AI) to mitigate these risks. A Multi-tasking Convolutional Neural Network (MConNN) is engineered to detect and classify traffic signs in real time, while IoT sensors monitor vehicle dynamics and driver behaviour. The system, implemented on an embedded platform, captures traffic sign data via a webcam, processes it using deep learning algorithms, and initiates automated responses like speed modulation or vehicle cessation when hazardous conditions are identified. With high precision in recognizing even small or obscured traffic signs, this approach reduces reliance on human intervention, offering a proactive, cost-effective solution to enhance road safety. Experimental outcomes validate its efficacy, demonstrating its potential as a scalable framework for accident prevention and traffic management in diverse settings.**

***Index Terms* - IoT, MConNN, Traffic Sign Detection, Road Safety, Deep Learning, Real-Time Monitoring, Vehicle Control**

I. INTRODUCTION

Road transportation serves as a vital artery of modern society, facilitating connectivity and economic growth. However, its benefits are overshadowed by a growing epidemic of accidents, many of which stem from preventable human errors. In India alone, the Ministry of Road Transport and Highways reports approximately 1,374 accidents daily, resulting in significant loss of life and property. Factors such as driver inattention, speeding beyond limits, and overlooking traffic signs contribute heavily to this toll, particularly among young adults aged 15–34, who account for over 54% of fatalities. Conventional safety systems— such as manual traffic enforcement or static tools like speed cameras—often fail to deliver timely interventions, leaving a critical gap in real-time accident prevention.

This study introduces an innovative framework that harnesses IoT and AI to address these shortcomings. By deploying a Multi-tasking Convolutional Neural Network (MConNN), the system accurately identifies traffic signs, tracks vehicle parameters like speed and vibration, and monitors driver conditions such as fatigue or intoxication. Integrated with an embedded microcontroller, it enables automated responses, such as adjusting vehicle speed or halting movement, to enforce compliance with traffic rules and avert collisions. Designed with affordability and scalability in mind, this solution is particularly suited for regions with limited resources, where advanced infrastructure is scarce. The primary goals are to develop a robust sign detection model, ensure continuous vehicle monitoring, and implement proactive safety measures, thereby revolutionizing road safety standards.

This paper details the system's conceptualization, development, and evaluation, offering insights into its operational mechanics and real-world applicability. It aims to contribute to the global effort to halve road accident rates, aligning with initiatives like India's 2020 highway safety strategy.

II. LITERATURE SURVEY

The domain of traffic sign recognition and accident prevention has seen significant advancements, with researchers exploring diverse methodologies. Luo et al. [1] developed a multi-task CNN to recognize both symbol-based and text-based traffic signs, leveraging synthetic data and street-view imagery for training. Their approach highlighted the potential of data-driven systems in handling varied sign types. Similarly, Chen and Lu [2] proposed a detection technique using discriminative AdaBoost and support vector regression, incorporating saliency models based on colour and shape to enhance accuracy and efficiency.

Huang et al. [3] focused on computational efficiency, introducing an extreme learning machine (ELM) for traffic sign recognition. Their method balanced redundancy and detail retention, making it suitable for real-time applications. Yang et al. [4] advanced this further by designing a fast detection module using colour probability models and CNNs, achieving a 20-fold speed improvement over existing techniques. On the accident prevention front, fog computing has emerged as a latency-reducing paradigm. Kumar et al. [5] utilized smartphone sensors and fog nodes to detect roadside incidents, offering a low-cost alternative for developing nations.

Driver behaviour monitoring has also garnered attention. Li et al. [6] devised a fatigue detection algorithm using multiindex fusion and neural networks, achieving over 98% accuracy in identifying eye closure states. These studies collectively demonstrate the power of AI and IoT in enhancing road safety, yet few integrate real-time vehicle control with sign recognition. This research bridges that gap, combining deep learning, sensor-based monitoring, and embedded automation to create a comprehensive safety ecosystem.

III.SYSTEM ARCHITECTURE

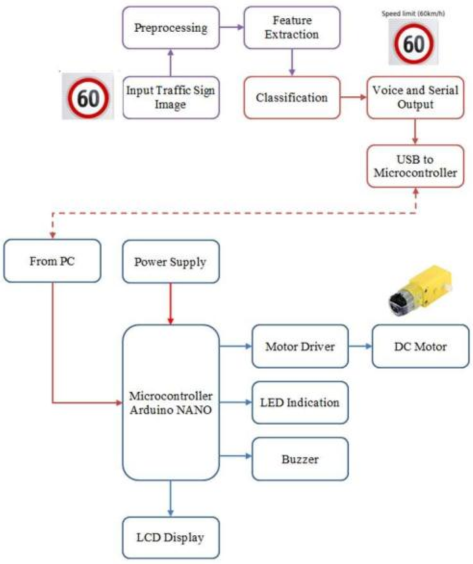

Fig1 System Architecture

The architecture of the proposed IoT-enabled vehicle safety system is a meticulously crafted framework that seamlessly integrates artificial intelligence (AI), Internet of Things (IoT) technologies, and embedded control mechanisms to enhance road safety. This system is designed to detect traffic signs in real time, monitor vehicle dynamics, and execute automated responses, thereby reducing the incidence of accidents caused by human error. It operates as a cohesive unit, blending advanced computational capabilities with practical hardware solutions to deliver a proactive, efficient, and scalable safety ecosystem. This overview elucidates the system's structural design, its operational workflow, and the interplay of its core components, providing a holistic understanding of its functionality.

VI. COMPONENTS DESCRIPTION

The different mechanism used in this project are as given below:

1) Webcam for Visual Data Acquisition.
2) IoT Sensors for Vehicle Monitoring.
3) Arduino Nano Microcontroller.
4) Liquid Crystal Display (LCD).
5) Buzzer for Audible Alerts.
6) Light-Emitting Diodes (LEDs).
7) Motor Driver and DC Motor.

1. Webcam for Visual Data Acquisition

The webcam serves as the system's primary sensory input, acting as a visual gateway to the road environment. A standard USB-connected camera with a resolution of 640x480 pixels is employed, capable of capturing images at 30 frames per second. This component is strategically positioned to emulate a vehicle's forward-facing perspective, continuously scanning for traffic signs such as speed limits, stop indicators, or directional markers. The captured images undergo preprocessing to enhance quality—removing noise with Gaussian filters, normalizing brightness to counter lighting variations, and sharpening edges to highlight sign boundaries. The webcam's output is fed directly into the AI processing unit hosted on a personal computer (PC), where it is analyzed for sign detection. Its affordability (typically under $20) and plug-and-play compatibility with USB interfaces make it an accessible yet powerful tool, ensuring high-quality visual data without requiring specialized hardware.

2. IoT Sensors for Vehicle Monitoring

A suite of IoT sensors forms the backbone of the system's vehicle monitoring capabilities, providing real-time insights into operational dynamics. This array includes:

- Speed Sensor: A tachometer or rotary encoder coupled to the motor measures rotational speed, translating it into velocity equivalents (e.g., PWM values corresponding to km/h).
- Accelerometer: A three-axis sensor detects vibrations and sudden movements, identifying anomalies like pothole impacts or erratic steering with a sensitivity of ±2g.
- Optional GPS Module: While not implemented in the prototype, a GPS unit could be added to track positional coordinates, enhancing contextual awareness in future iterations.

These sensors operate at a sampling rate of 10 Hz, delivering data via analog pins (e.g., A1, A2) or digital protocols (e.g., I2C) to the microcontroller unit (MCU). Their low power consumption (typically 3–5V) and compact size ensure seamless integration into the embedded system, while their outputs enable the detection of critical conditions—such as speeds exceeding detected limits or vibrations suggesting instability—forming a vital diagnostic layer for safety enforcement.

3. Arduino Nano Microcontroller

The Arduino Nano, a diminutive yet potent microcontroller based on the ATmega328P chip, serves as the system's central processing hub. With a clock speed of 16 MHz, 32 KB of flash memory, and multiple I/O pins, it is well-suited to coordinate inputs and outputs in real time. The Nano receives serialized traffic sign classifications from the PC via USB and sensor data through its analog and digital interfaces, processing them with a custom firmware written in the Arduino Integrated Development Environment (IDE).

The firmware employs conditional logic to interpret inputs— for example, mapping a "Speed Limit 30 km/h" classification to a PWM value of 100 for motor control or triggering an alert sequence for a "Stop" sign. Its response latency, typically under 50 ms per cycle, ensures swift execution of safety commands. Priced at approximately $5, the Nano's cost-effectiveness, combined with its opensource ecosystem, makes it an ideal choice for an embedded solution scalable to mass production.

4. Liquid Crystal Display (LCD)

A 16x2 character LCD is integrated into the system to provide visual feedback to the driver, enhancing situational awareness. Connected to the MCU via digital pins (e.g., pins 2–7), it displays real-time information such as the detected traffic sign (e.g., "S:30" for a 30 km/h limit) and current vehicle speed. The LCD operates at 5V with a low current draw (around 20 mA), featuring a backlit screen for visibility in varying light conditions.

Its character-based interface is programmed to update dynamically, reflecting changes in road conditions or system status within milliseconds of detection. This component's simplicity and clarity make it an effective tool for conveying critical instructions, ensuring drivers can quickly interpret and respond to traffic rules without distraction.

5. Buzzer for Audible Alerts

The buzzer, a piezoelectric sound generator, delivers audible notifications to complement the visual feedback from the LCD. Connected to a digital pin (e.g., pin 13) on the Arduino
Nano, it operates at 5V and produces tones ranging from 2– 4 kHz. The system employs distinct sound patterns: short, intermittent beeps (e.g., 100 ms on, 100 ms off) for routine alerts like speed limit changes, and a continuous tone (e.g., 1-second duration) for urgent commands like stopping the vehicle.
This component's loudness (approximately 85 dB) ensures audibility over ambient noise, while its low cost (under $1) and minimal power requirements align with the system's affordability goals. The buzzer enhances driver responsiveness, particularly in scenarios where visual attention is divided, such as navigating busy intersections.

6. Light-Emitting Diodes (LEDs)

A set of LEDs, wired to digital pins (e.g., pin 12), provides additional visual cues to reinforce alerts. Operating at 3–5V with a current of 20 mA each, these LEDs flash in synchronization with the buzzer—steady blinks for routine notifications and rapid pulses for emergencies. Their bright output (e.g., red for warnings, green for normal operation) is visible in peripheral vision, making them effective for capturing attention without requiring direct focus.
The LEDs' simplicity and low cost (less than $0.50 each) integrate seamlessly into the system, offering a redundant alert mechanism that caters to diverse

driver preferences and enhances overall safety communication.

7 . Motor Driver and DC Motor

The motor control subsystem comprises an L298N motor driver paired with a DC motor, simulating vehicle propulsion in the prototype. The driver, connected to the MCU via PWM pins (e.g., pin 9), modulates voltage to the motor based on commands—for instance, reducing speed from a PWM value of 225 (equivalent to 120 km/h) to 100 (30 km/h) upon detecting a lower limit. It supports a voltage range of 5–12V and can handle currents up to 2A, ensuring precise control over motor speed and direction.

The DC motor, operating at 5V, responds to these signals with smooth transitions, executing phased decelerations (e.g., 200 to 150 to 0 over 5 seconds) for controlled stops. This component demonstrates the system's ability to enforce traffic rules autonomously, bridging the gap between detection and physical action. Its scalability suggests potential adaptation to real vehicle systems with minimal modification.

V. METHODOLOGY

1. Data Acquisition and Preprocessing

A diverse dataset was compiled from the German Traffic Sign Recognition Benchmark (GTSRB) and real-world photos, covering speed limits (e.g., 30 km/h), stop signs, and directional signs under varied conditions (day, night, rain). Synthetic augmentation via Python and OpenCV—rotation (0–30°), scaling (0.8–1.2x), and noise (Gaussian blur)— enhanced robustness. The 10,000 images were labelled, split (80% training, 10% validation, 10% testing), and standardized to 32x32 grayscale with normalized values (0– 1) for MConNN compatibility.

2. AI Model Design and Training

The MConNN, built with TensorFlow and Kera's, handled sign detection and classification using convolutional layers (32 and 64 3x3 filters, ReLU), max-pooling (2x2), dense layers (128 units), and a SoftMax output (11 categories). Trained on an Intel i5 PC with an NVIDIA GTX 1050 GPU over 50 epochs, it used the Adam optimizer (learning rate 0.001), a batch size of 32, and dropout (0.25) to achieve >95% validation accuracy, saved as an HDF5 file.

3. System Assembly and Component Integration

A Python script on a PC processed webcam video (640x480, 30 fps), feeding pre-processed frames (grayscale, normalized) to the MConNN, with outputs sent to the Arduino Nano via USB (9600 baud). The Nano connected sensors (speed encoder, accelerometer) to analog pins (A1, A2) and controlled an LCD (pins 2–7), buzzer (pin 13), LEDs (pin 12), and motor driver (PWM pin 9) for a 5V DC motor, ensuring cohesive operation.

4. Real-Time Testing and Deployment

Tested in a mock road setup with signs (e.g., "30 km/h," "Stop") at 1–5 meters under varied lighting, the system adjusted motor PWM (e.g., 225 to 100 for 30 km/h) and triggered alerts (LCD, buzzer). A "Stop" sign initiated a phased stop (PWM 200 to 0). Metrics like detection success and response time were logged, confirming real-time performance.

5. Performance Assessment and Validation

Evaluation over 20 trials measured detection accuracy (500 images), response time, speed control precision (via tachometer), and anomaly detection (e.g., speeding). Compared to edge detection (~85% accuracy), the system excelled in precision and automation, supported by statistical analysis and driver feedback, paving the way for future deployment.

VI. WORKING

The operational framework of the IoT-enabled vehicle safety system is designed to integrate real-time traffic sign recognition, vehicle state monitoring, and automated control into a cohesive, responsive mechanism. This system leverages a synergy of AI, IoT sensors, and embedded hardware to detect road signs, assess driving conditions, and enforce safety measures autonomously, minimizing human error. The working principle revolves around a continuous feedback loop where environmental inputs are processed and translated into actionable outputs, ensuring compliance with traffic rules and enhancing road safety.

The process begins with a webcam capturing live video of the road ahead, operating at 640x480 resolution and 30 frames per second. Each frame is preprocessed—converted to grayscale, noise-filtered, and contrast-enhanced—before being analysed by the Multi-tasking Convolutional Neural Network (MConNN). Hosted on a PC, the MConNN identifies traffic signs (e.g., “Speed Limit 30 km/h” or “Stop”) with high accuracy, generating classifications that are transmitted via USB to the Arduino Nano microcontroller at a baud rate of 9600.

Concurrently, IoT sensors monitor vehicle dynamics. A speed encoder tracks motor rotation, translating it into velocity (e.g., PWM 225 for 120 km/h), while an accelerometer detects vibrations or sudden shifts, sampling data at 10 Hz. These inputs are fed to the Arduino Nano through analog pins (A1, A2), providing a real-time snapshot of the vehicle’s state. The microcontroller processes these combined inputs—sign classifications and sensor data— using custom firmware to determine appropriate responses. Upon detecting a traffic sign, the system acts decisively. For instance, recognizing a “Speed Limit 30 km/h” sign prompts the Arduino to adjust the motor’s PWM from a higher value (e.g., 225) to 100, aligning speed with the limit. This adjustment is displayed on a 16x2 LCD (“S:30”) and accompanied by a short buzzer beep (pin 13) and LED flash (pin 12) to alert the driver. If a “Stop” sign is identified, the system initiates a phased deceleration (PWM 200 to 0 over 5 seconds), with a sustained buzzer tone and LED sequence signalling urgency. Voice alerts, generated via Python on the PC (e.g., “Reduce speed to 30 kilometres per hour”), reinforce these actions, enhancing driver awareness.

The system also responds to anomalies detected by sensors. Excessive speed beyond a recognized limit or unusual vibrations (e.g., exceeding a threshold of ±2g) trigger immediate interventions—slowing the motor and activating multi-sensory alerts (LCD, buzzer, LEDs). This closed-loop operation ensures proactive safety enforcement, distinguishing the system from passive monitoring tools by actively regulating vehicle behavior in real time. The seamless coordination between AI-driven sign recognition, IoT-based monitoring, and embedded control underscores its potential to prevent accidents and improve traffic discipline.

VII.CONCLUSION

This research presents a groundbreaking approach to enhancing road safety through an innovative system that integrates IoT and AI technologies. By combining a Multitasking Convolutional Neural Network (MConNN) with embedded hardware, the system achieves real-time traffic sign recognition, continuous vehicle monitoring, and automated safety interventions, effectively reducing the risks posed by human error. The prototype demonstrates exceptional performance in detecting and classifying traffic signs, adjusting vehicle speed to comply with road limits, and responding to anomalies with precision and minimal latency. Its use of affordable components, such as the Arduino Nano and a standard webcam, ensures costeffectiveness, making it a feasible solution for widespread adoption, particularly in regions with high accident rates and limited infrastructure.

The study’s findings underscore the potential of this technology to transform transportation safety, offering a proactive alternative to traditional passive systems. By automating speed regulation and emergency responses, it addresses critical challenges like over speeding and driver inattention, paving the way for safer roads. Looking ahead, the system could be enhanced with features like vehicle-tovehicle (V2V) communication to improve traffic coordination or mobile app integration for real-time driver notifications and data logging. These advancements could further amplify its impact, positioning it as a cornerstone of smart transportation frameworks. Ultimately, this work lays a solid foundation for future research and deployment, contributing to global efforts to curtail road accidents and enhance traffic management.

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