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IOT BASED SPEED CONTROL MONITORING AND ACCIDENT AVOIDANCE USING AI TRAFFIC SIGN DETECTION

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Abstract -- Revolutions occur everywhere in the world. Road mobility is the most crucial component of contemporary communication. Accidents and traffic congestion are becoming major problems as a result of the growing population. Generally speaking, people are unable to receive early alerts about traffic congestion. We later noticed a traffic bottleneck as we approached a particular location. Human-caused traffic accidents are not uncommon these days. Due to the growing number of vehicles and the lenient enforcement of traffic laws, human error plays a significant role in accidents and fatalities on Indian roads. In those mishaps, they also lose our lives and possessions. As a result, tired drivers who are not following the law are involved in traffic accidents. This study recommends using the Multi-tasking Convolutional Neural Network (MConNN) model to recognize traffic signs and vehicle characteristics including location and vibration. The driver's model is identified by physical attributes and traffic indications. These features have been modified to enable speed control and track the vehicle's condition. This paper presents a unique detection method, called MConNN, that can

reliably detect speed in real time, identify small traffic signals, assess vehicle attributes, and detect whether a driver is under the influence of alcohol.
Keywords : MConNN, Speed Control, Traffic Sign, Iot ,AI

I. INTRODUCTION

Driver mistake is the most frequent cause of motor accidents that pose a risk to public safety. For a variety of reasons, many drivers struggle to maintain control of their vehicles, which can result in risky situations and occasionally fatalities. Car accidents can be caused by a variety of factors, including driving too quickly, being intoxicated, and being preoccupied with things like texting, talking to others, or playing with children. Avoiding dozing off while driving is one of the most crucial things. Most people may not realize how deadly driving when fatigued may be, even though they are aware of the risks of driving after drinking.

According to a 2015 report by India's Ministry of Road Transport and Highway, 1,374 accidents and more than 400 fatalities occur daily. Approximately 57 traffic events lead to 17 car accident fatalities every hour. This suggests that 54.1 percent of fatal auto accidents involve individuals between the ages of 15 and 34. The Highway Government of India, the Ministry of Road Transport, and the Indian government are collaborating to develop a plan aimed at halving the number of highway fatalities and accidents by 2020.

Traffic indicators are very crucial when driving. They act as alarms, route directions, and traffic controllers. There will be fatalities if this can be avoided. A automobile may miss traffic signs due to unfavorable traffic circumstances, which could result in crashes. In these situations, an automated road sign Detection comes next. A traffic code will often outline the four primary types of traffic signs: duty, warning, restriction, and instructional. These red flags, which may take on a variety of shapes and colors, are symmetrical triangles with an upright vertex. They are bordered with red and have a white foundation. Circular shapes with a red border and a white or blue background are used as warning signs.

A circle on a white or blue backdrop is an obligation symbol. Each and every one of the informative signage has the same hue. To find the sign in the picture, we must be cognizant of both the color and the shape. Traffic signs can be kept in their proper locations, distracted drivers can be warned, and potentially dangerous behavior can be discouraged by being able to recognize them. By greatly increasing their degree of safety, real-time automatic speed sign identification and recognition helps drivers. These days, the market's demand for cutting-edge applications like driver assistance systems (ADAS), autonomous driving, mobile mapping, etc., has also increased interest in traffic sign identification among large enterprises. This number would be far greater if there were no traffic signs. Naturally, autonomous vehicles have to abide with traffic laws.

Traditionally, computer vision techniques were used to identify and classify traffic indications. Significant human labor was needed to manually construct key features in photographs. In order to solve this issue, we used deep learning to train a model that can decipher traffic signs with high accuracy and discover which attributes are most useful on its own. With a 98% success rate on the test set, I demonstrate in this post how to build a deep learning architecture for traffic sign identification.

II. RELATED WORK

Autonomous driving systems have been made possible by technological advancements, which necessitates new concepts to increase traffic safety and address transportation-related problems. This study evaluates and compares the YOLOv7 and YOLOv8 models from the YOLO family's performance in recognizing traffic signs, which are crucial for road safety. [3] The study uses a sizable dataset from the Google Earth platform to examine the faults and successes of both methods. YOLOv8 has excellent performance in challenging traffic sign detection settings, with corresponding mAP, accuracy, and recall scores of 0.807, 0.815, and 0.866. In challenging situations, YOLOv7 outperforms YOLOv8 despite displaying competitive outcomes. The study provides a comprehensive analysis of both methods, highlighting their benefits, drawbacks, and potential directions for traffic sign detection research.

Since accuracy and consistent performance are critical to vehicle security, traffic sign recognition is a crucial component of autonomous driving. In light of the YOLOv5 technique, this work suggests an improved multi-scale traffic sign identification calculation, MMW-YOLOv5, to further develop the distinguishing proof execution of multi-scale traffic sign focuses. [5]. The inaugural use of a multi-scale fusion network (MSFNet) on the neck significantly improves the algorithm's fusion skills for multi-scale properties and its ability to distinguish small objects. Second, to get rich multi-scale feature information and simplify multi-scale target recognition, the C3 bottleneck structure in the trunk and neck is replaced with the multi-scale feature extraction bottleneck module (MSFEBM), which processes small-scale feature maps.

In order to enhance traffic sign recognition (TSR), we present in this work a cross-space not many shot in-setting learning technique based on the multimodal massive language model (MLLM). First, we use an extraction module and a Dream Transformer Connector to build a traffic sign detection network. This will allow us to separate the traffic signs from the original street photographs. [7] A cross-space not many shot in-setting learning technique is offered in view of the MLLM in order to further enhance the presenting strength of crosscountry TSR and reduce the requirement for information preparation. The suggested method uses layout traffic signs to generate matching representation texts in order to improve MLLM's fine-grained traffic sign recognition evidence.

Video-based tactics are becoming more and more popular because to the availability of high-goal cameras. For autonomous driving frameworks to function, traffic sign positioning and recognition are crucial. In this research, we offer a deep CNN-based method for recognized proof and continuous traffic sign recognition in video transfers. Using a deep CNN architecture, we provide a multi-stage system for object finding, sign recognition, and video pre-handling. [10] The algorithm is trained on a huge dataset of elucidated video summaries and then tested on a smaller dataset to see how well it performs. The results show that the suggested strategy is very accurate in distinguishing between various traffic signals. This tactic can aid in advancing street security and may be used with autonomous driving frameworks.

The goal of this research is to use PC vision techniques to create a trustworthy traffic light differentiating framework. To identify and differentiate traffic signals in real time, the suggested solution makes use of deep learning computations and image processing techniques. [12] A comprehensive brain network model is further constructed by motion learning using a large collection of images of traffic signals with comments. To locate and identify traffic signals inside input outlines, the constructed model uses cutting-edge object identification techniques. Then, by using photo treatment techniques to remove fake up-sides, the acknowledgment ratings are raised. The method ensures robust detection even in testing scenarios by combining precise analysis to track traffic lights across frames.

III. METHODOLOGY

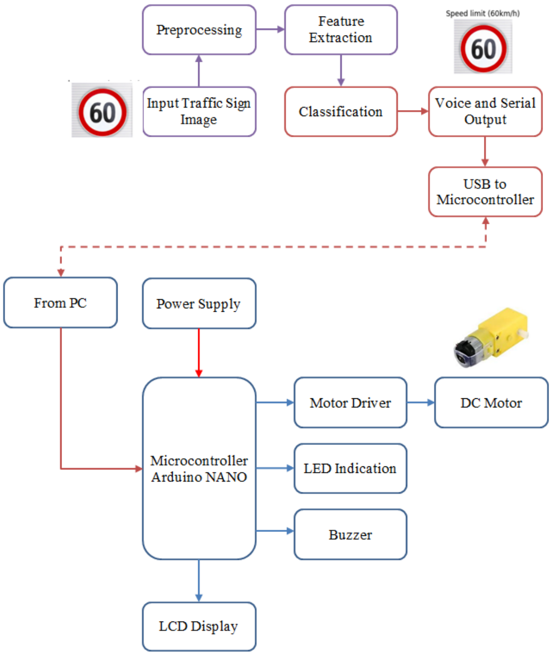
A. Proposed Method

It is necessary to continuously assess factors such stopping accessibility, public transportation, traffic density, and street obstruction in order to achieve the goal of a more bright city. The introduction of developments in vehicular systems administration, including as IEEE 802.11p and WAVE, has made it possible to easily obtain this data from vehicles in urban areas. As a less expensive alternative to installing permanent side-of-the-road infrastructure, abandoning vehicles can serve as the hub for organizing moving cars, collecting, merging, and exchanging their data. This work provides creative methods for letting cars organize themselves into attractive car-help groups throughout a city.

By redistributing the roles of roadside units between vehicles as needed, these mechanisms can continuously optimize the network of parked cars, modify the battery consumption of individual cars, and have a multi-criteria decision-making process that can be focused on critical network performance metrics. These makes these mechanisms unique.

We also provide the first comprehensive evaluation of the feasibility of such a framework, including an exploratory validation of important self-association concepts and a reasonable reproduction presentation of halting, portability, and correspondence. This study identifies areas of strength for left-hand cars that can serve as a replacement for long-distance side-of-the-road foundations and build networks that enable more intelligent mobility and adaptability. To improve YOLOv3's identification skills, we suggested MSA_YOLOv3, a remarkable recognition technique that can recognize small traffic signs in a variety of scenarios.

B. Proposed Block Diagram

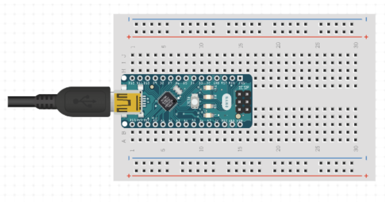


Proposed Block Diagram

C. Hardware Descriptions

Arduino Nano

The Arduino Nano, built on the ATmega328P, is a small, feature-packed, and breadboard-friendly circuit board. It is smaller than the UNO board, yet it is just as functional and connected.

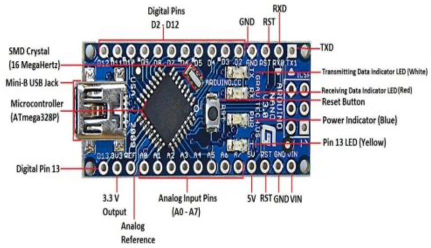


Arduino NANO Interface

The Arduino Programming (IDE), an Integrated Development Environment that can be used online and offline and is compatible with all of our sheets, is used to modify the Arduino Nano. See the Beginning page to learn more about how to begin using the Arduino programming.

The Arduino Nano is comparable to the Arduino Duemilanove in many aspects, although having a different packaging. The Arduino Nano is built utilizing an ATmega328P computer chip, just as the Arduino UNO. The primary distinction between the two is that the UNO board comes in a 30 pin PDIP (plastic double in-line bundle) layout, whilst the Nano is offered in a 32-pin TQFP (plastic quad level pack) format. Two more pins complete the ADC capabilities, even though the Arduino Nano has eight ADC ports instead of the UNO's six. Unlike other Arduino sheets, the Nano board contains a smaller-than-normal USB connector instead of a DC power port.

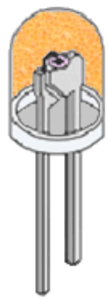
- **Arduino Nano Pinout Description**



Arduino Nano pin Description

LED (LIGHT EMITTING DIODE)

One of the most popular types of semiconductor diodes available today are light-emanating diodes, or LEDs for short. On variety screens and televisions, they are usually visible. They are the most transparent type of diode; when a forward current is given to them, they can produce infrared light that controllers cannot see, precise light at a rather low transfer speed, or detectable light at a few different frequencies.



LED

Semiconductors called light-radiating diodes can then convert electrical energy into light energy when used in a forward-one-sided manner.

USB WEBCAM

The method typically uses a webcam to take multiple pictures. We have the option to store these collected images as distinct frames in our system. The generated frames are fed into facial recognition software. In other words, the image's eye, which serves as its focal point, is removed.

Web camera

BUZZER

Buzzer

By reversing the piezoelectric motion, the piezo buzzer generates sound. The fundamental idea is that strain or pressure variations are produced when an electric voltage is placed across a piezoelectric material. These buzzers can be configured to activate when a switch is flipped on, a counter signal is received, or a sensor input is recognized. Alarm circuits are another application for them. The buzzer continuously produces the same loud noise when voltage is introduced. Two conductors encircle piezo crystals. In response to an applied potential, these crystals exert a pulling force on one conductor and a pushing force on the other.

V. RESULT AND DISCUSSION

Farmers' difficulties in obtaining financial protection against crop loss have been effectively addressed by the installation of the agriculture insurance management system. Applying for crop insurance, confirming claims, and making sure farmers receive their money on schedule are all made easier by the system. The findings show that the automated insurance application and verification procedure improves transparency and drastically cuts down on delays. Images of damaged crops may be uploaded by farmers with ease, and the method guarantees prompt insurance company certification. This minimizes fraud and errors by reducing the amount of manual interaction needed for claim processing.

The integration of digital records also provides greater accessibility for farmers and insurance providers. When farmers can track the status of their claims in real time, they are more inclined to trust insurance programs and take part in them. In order to guarantee that compensation reaches impacted farmers effectively, the system also promotes improved collaboration between government organizations and insurance firms. This digital approach is more dependable and easier to use than traditional insurance claim procedures, which entail a lot of paperwork and lengthy processing times. Future developments could include blockchain-based claim verification, AI-driven damage assessment, and predictive analytics for improved risk management.

VI. CONCLUSION

This initiative has made the driving aid system available. The fundamental concept is to identify and categorize traffic signs using an input image. The image processing method used by this system is based on the CNN algorithm. Ultimately, a database of road sign patterns is used to identify and classify these possible road signs, and the speed is adjusted accordingly. The way this method works depends on the quality of the input image, which includes the size, contrast, and appearance of the signs in the image. This method totally substitutes an automated process for the current human one. As a result, it reduces human error and improves precision, computing efficiency, and reliability. This article outlines the steps involved in creating a self-responsive robotic car. The different hardware components' modes of operation are explained.

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