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Advanced Vehicle Detection and Tracking on Roads Using Deep Learning

Dr. Sruthi[1], Sana Afreen[2], Rajalingola Sai Charan[3], Gajula Surya[4], Yada Shreya[5]
[1]*Associate Professor, Department of CSE (Artificial Intelligence & Machine Learning), CMR College of Engineering & Technology, Hyderabad, Telangana State, India.*
[2]*Assistant Professor, Department of CSE (Artificial Intelligence & Machine Learning), CMR College of Engineering & Technology, Hyderabad, Telangana State, India.*
[3, 4, 5]*B. Tech Students, Department of CSE (Artificial Intelligence & Machine Learning), CMR College of Engineering & Technology, Hyderabad, Telangana State, India.*

Abstract: The world has been overtaken by artificial intelligence (AI), machine learning, and deep learning, which are affecting every aspect of our lives, including our need for companionship and the growth of smart cities and communities. Though tremendous progress has been made in fields like healthcare and education, transportation. Transportation is a significant barrier that has a huge financial and human cost on a worldwide scale. Traditional methods of assessing traffic on roads, which rely on inductive loops, don't give much information and can't control traffic in real-time. This study describes how the transportation sector could undergo a deep learning revolution. Deep learning techniques, including image and video analysis, have the potential to revolutionize road traffic monitoring by enabling computers to recognize traffic congestion, enhance road safety, and address various other concerns. The integration of deep learning technologies promises a new era of data-driven solutions for transportation-related issues, which could ultimately result in safer, more effective, and economically sustainable societies in the face of over a million annual fatalities and trillions of dollars in damages. In order to address these problems, this paper shows how well YOLOv3 detects automobiles and how well Darknet53 tracks these vehicles while they are on the road.
Keywords: YOLOv3, Darknet53, monitoring, deep learning.

I. INTRODUCTION

Artificial intelligence (AI), which now influences every area of our lives, has profoundly changed the way we live. Machine learning and deep learning are revolutionizing smart cities and communities and tackling many long-standing problems in domains such as education and health. Even though it still causes incredible harm over a million deaths, millions of injuries, and trillions of dollars in damages annually worldwide. Transportation is the backbone of today's society and economy. Inductive loops are used in conventional traffic measurement and tracking systems to provide the certain fundamental traffic data, such as average speed, number of vehicles, and traffic flow.

Conventional technologies are not capable of supporting the real-time monitoring and control of traffic on roads. These loops being laid down on the roadways act as sensors that can pick up key traffic data such as the average speed of vehicles, the number of vehicles, and traffic flow patterns. Through exploitation of the data gathered by the inductive loops, transportation authorities will have valuable insights into traffic dynamics which will allow informed policy-making and optimization of the transport network for efficiency and safety institutionalization. Among the numerous industries that deep learning has the potential to revolutionize is transportation. Automated traffic monitoring using image and video analysis is one of the deep learning driving strategies. These methods can be used for a variety of purposes, including traffic identification and increased road safety.

In this we are using COCO dataset, it is a big set of images that covers various objects and scenes and shows how the objects are used in different situations and settings. Every image in the dataset is annotated with bounding boxes that show the locations of objects as well as segmentation masks that show the detailed outline of each object. The main advantage of the COCO dataset is the fact that it is a complete representation of object categories with different objects included which are found in real-life situations. Firstly, diversity in the dataset is what makes it highly valuable when it comes to training and evaluating object detection and segmentation models because this allows models to perform accurately in a variety of visual contexts.

The project's objective is to demonstrate how traffic flow data from deep learning can enhance road traffic monitoring. The detections are performed on each frame by using YOLOv3 object detection algorithm and displayed on the screen with bounding boxes.Advanced technologies allow for the detection of items on the road, such as the YOLOv3 model that makes use of Darknet-53 to detect moving vehicles.

II. RELATED WORK

A. A Multi-Inductive Loop Vehicle Identification System For Laneless And Heterogeneous Traffic

A novel inductive loop sensor is presented in this research that can be utilized to support traffic management system in making the most use of accessible roads by detecting vehicles in conditions of heterogeneous and less lane-disciplined traffic. The key component needed to sense heterogeneous and less lane-disciplined traffic is the loop sensing sensor presented in this study, which can identify both big (like buses) and small (like bicycles) vehicles occupying any available space in the roadway. A multiple loop systems with a new induction loop sensor construction is developed to achieve the sensing of both large and small vehicles. In addition to detecting and classifying different types of vehicles, such as cars, buses, motorcycles, scooters, and bicycles, the suggested sensor structure also makes it possible to precisely count the number of vehicles, even when there is mixed traffic flow. The multiple loop sensing system prototype has been designed and put through testing. According to field tests, the prototype was able to accurately count the quantity of each type of vehicle and effectively identify all vehicle types. It has been demonstrated that the suggested sensor system is suitable for all types of traffic.

B. Tracking Heavy Vehicles Using Inductive Loop Signature And Weigh-In-Motion Technologies

In this paper we mainly deal with heavy vehicles which are tracked based on Weight-In-Motion. On highways, the weigh-in-motion technologies (WIM) are playing a vital role in collecting information about heavy carriers. Since WIM systems are the most advanced and expensive data-collecting tools, one has no choice but to efficiently use the available data. The monitoring of WIM stations is an important procedure that helps provide credible and trustworthy data collection. Focusing on this, our research introduces a new approach to heavy truck tracking. Data from inductive loop signatures and WIM sensors are combined to form a thorough tracking system. The blend of these two different pieces of information provides an innovative multilayer vehicle reidentification system that is able to achieve increased tracking accuracy and reliable performance. This revolutionary technique combines the benefits of both WIM technology and inductive loop signature analysis, demonstrating a prospective road for better operability and effectiveness of heavy vehicle control on highways.

C. An Autonomous Inductive-loop vehicle sensor that makes use of an Affordable Microcontroller

This paper presents a circuit working on a new concept in designing a vehicle sensor that employs an inductive loop as a resonant structure. The bit stream resulting from this circuit is acquired by an inexpensive microcontroller with a slow ADC framework. The operation of this sensor is centered on its auto calibration response which relies on the K-means clustering algorithm for correct and resultant object detection. Firstly, the achievable error stresses the high precision level of subcompact cars being detected. This paper projects this circuit design, along with the methodology, thereby contributing to the field of automobile sensor technologies. The design can be made cost-effective and reliable in detecting vehicles with accuracy to a large extent. Using the merged design rationales, microcontrollers, and new approaches to calibration, this study provides the fundamentals for improved vehicle detection and can be applied to various sectors from traffic monitoring to intelligent transportation systems.

D. Models for Estimating Traffic flow using cellular Phone Data

In transportation research, traffic volume is a measure of demand, and it is typically obtained by the use of on-road (fixed) sensors like cameras, inductive loops, and so forth. Fixed sensors are only deployed on a subset of links because it is not possible nor financially feasible to install them on every road. To gather traffic data, cellular phone tracking has become a popular issue during the past few years. Alternative techniques for detecting phones in motion are offered by cellular systems, which do not have the expense or coverage restrictions of those infrastructure-based alternatives. When compared to alternative options, using current cellular systems to measure traffic volume has a significant advantage because it eliminates the need for costly new hardware installations of sensors, since many mobile phones serve as probes. This research uses phone call data that is anonymous to present a series of models for estimating the number of automobiles that are moving between cells. Terms about users' calling habits and additional features of the phenomenon, such as hourly calls and vehicle intensity, are included in the models in their functional form. For the field test, a collection of intercell borders with various traffic backgrounds and characteristics was chosen. According to the experiment results, one can obtain realistic estimations by comparing the volume measurements obtained from detectors situated inside the same research region. An easily available, quick, and inexpensive substitute for obtaining volume data on intercell boundaries is the movement of phones during calls.

III. SYSTEM REQUIREMENTS

A. Hardware Requirements

1) Processor – intel i7-8 core or above
2) Speed – 1.1 Ghz
3) RAM – 16 GB and Above.
4) Hard Disk – 500 GB or above

B. Software Requirements

1) Windows
2) Python
3) Visual Studio Code
4) OpenCV
5) TensorFlow
6) Anaconda Navigator

IV. METHODOLOGY

This study is a way how to detect and track the vehicles on the road .

A. Dataset Collection & Preprocessing

A pretraining process is applied to the YOLO weights file using the COCO (Common Objects in Context) image dataset, which is a large collection of visual contexts with a variety of vehicle kinds included.

In order to provide the model with the necessary discriminative skills to recognize and classify different vehicle entities with accuracy, this proactive training phase is essential.

Because it gives the model a sophisticated understanding of the visual cues unique to cars, the careful preparation of this data corpus is crucial to preparing it for tasks involving reliable detection and ongoing monitoring. As such, the preliminary stage not only strengthens the model's performance but also supports its flexibility in dynamically detecting and tracking vehicle motions in a variety of environmental contexts.

B. Vehicle Detection

The YOLOv3 detection technique is used in our model for detection. YOLO is our choice due to its accuracy and speed, particularly when dealing with comparatively larger items.

Given the characteristics of our data, we think YOLO is a good option. The YOLOv3 object detection technique is used to perform the detections on each frame, and bounding boxes are used to display the results on the screen. All vehicles, including motorcycles, buses, cars, cycles, trucks, and trains, are kept out of the detections by filtering them.

The YOLO machine learning technique locates objects in an image by using properties that a deep convolutional neural network has learned.It makes it possible for the object detection model to examine the entire image during testing. This indicates that the predictions are influenced by the image's global context.

Based on how closely a region resembles established classifications, YOLO and other convolutional neural network algorithms "score" it.

C. Vehicle Tracking

We are employing Darknet53, a deep neural network architecture that is frequently utilized for a variety of computer vision tasks, especially in the area of object identification and classification, for tracking purposes.

It is a 53-layer. One of the well-known object identification technique, YOLOv3, uses Darknet-53 as its backbone network. The method tracks each identified object by using the detection outputs from the preceding phase. The quality of detection results determines tracking accuracy when using a detection technique.

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D. Block Diagram

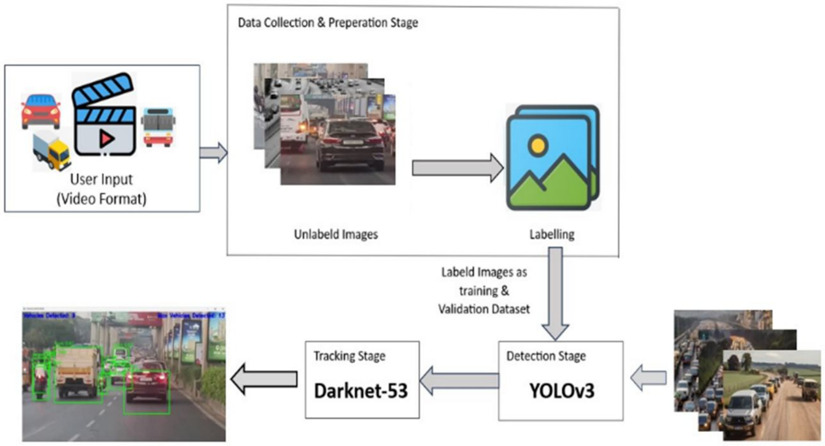

Fig 1: System block diagram

V. RESULT AND DISCUSSION

First we need to select the video, then YOLOV3 and Darknet-53 will start detecting and tracking the vehicles also we can see the number of vehicles tracked within a frame which can be seen in the below screenshot.

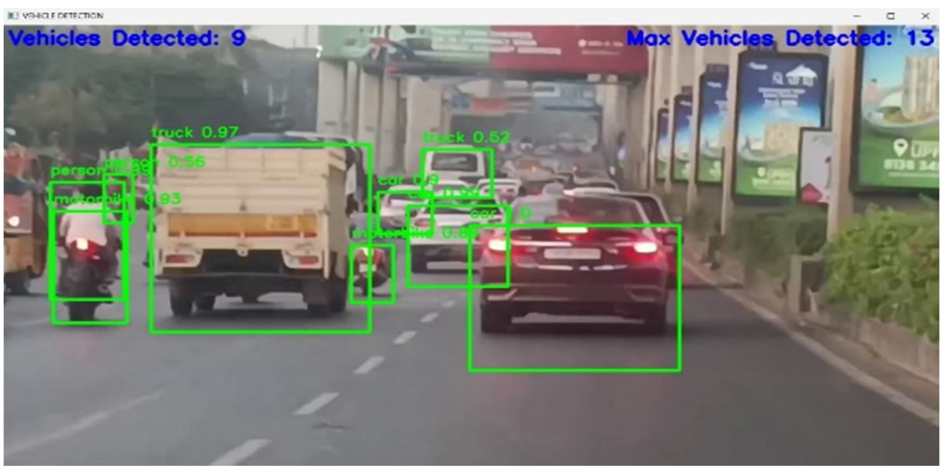

Fig 2: Detecting and tracking the vehicles

The below screenshot shows graphical representation of the output.

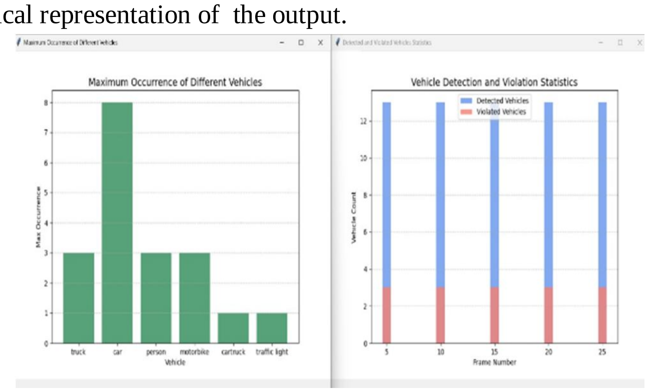

Fig 3: Results

VI. CONCLUSION

The core objective of our project is the identification of moving vehicles and the subsequent distribution of relevant data related to them. To support this effort, we have implemented features that are designed to identify instances of traffic violations, which will increase the project's usefulness in encouraging obedience to laws and regulations. Additionally, as we envision a forward-thinking course, our project will incorporate OCR (Optical Character Recognition) to deduce vehicle identity from license plates, expanding the project's reach and effectiveness. The integration of our technology with autonomous vehicles represents a paradigm change in traffic management, whereby dynamic modifications in vehicle trajectories are informed by real-time detection data, resulting in safer and more efficient transportation ecosystems. Furthermore, the quest for increased precision is supported by the application of state-of-the-art computational systems, which guarantees the stability and dependability of our vehicle detecting systems. Our research is well-positioned to drive revolutionary developments in the fields of regulatory compliance and vehicle surveillance as we work through the complex intersection of technology innovation and societal demands.

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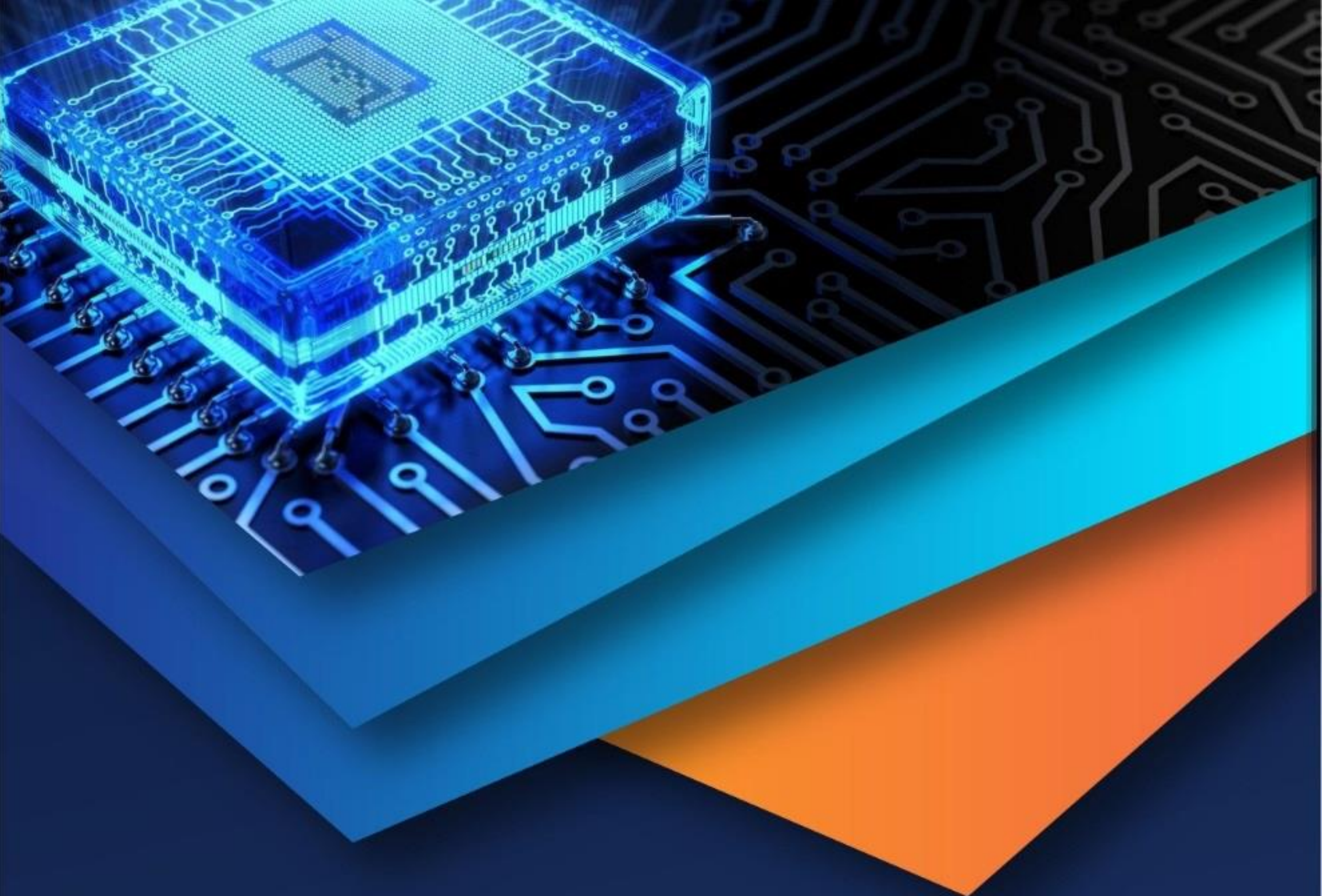

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