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Helmet Detection using ESP 32 Camera and Raspberry Pi

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***Abstract*— Helmet use among the motorcyclists is of paramount importance in ensuring safety on the road and is a crucial factor in reducing head injuries. There is a need for a new approach in this regard. This study, therefore, focuses on an innovative method that integrates advanced technology with a helmet detection system to investigate the capability of deploying these advanced algorithms, such as YOLO, FOMO, ResNet50, and MobileNet50, with an ESP32 camera platform. It aims to develop an automatic system for real-time detection of people wearing helmets to ensure compliance with this safety measure. Utilizing the ESP32 camera to capture image data and perform tasks, such as object detection and classification, will significantly strengthen road safety measures and reduce motorcycle-related accidents. In this study, the design, implementation, and evaluation of the system will be explained so that its potential in enhancing traffic safety and mitigating death resulting from road accidents will become apparent. Utilizing both ESP32 and Raspberry Pi makes the system even more effective and stronger, greatly contributing to road safety.**

***Index Terms*—Helmet Detection, ESP32, Mobilenet, Resnet50, YoloV8, FOMO, Raspberry Pi**

I. INTRODUCTION

Improving road safety remains a concern of utmost importance across the world due to the high percentages of accidents and head injuries among motorcyclists. The enactment of helmet usage regulations has come out to be one of the critical strategies that address these risk factors and protect public health. However, despite these relentless efforts, there still exists a need for innovative solutions that make use of cutting-edge technology to magnify safety measures on the roads.

In this light, the current study, therefore, offers a new approach in the form of the development of a comprehensive helmet detection system. Such a system represents the convergence of state-of-the-art technology and proactive road safety initiatives with the purpose of revolutionizing the way helmet enforcement is done.

In this regard, this system has utilized deep learning models such as YOLO, FOMO, ResNet50, and MobileNet50 with the versatile ESP32 camera platform and, alongside, Raspberry Pi. Such a combination of these state-of-the-art models and hardware makes it possible to enable the system automatically to detect people wearing helmets in real time, thus encouraging the people to comply with safety regulations and develop a culture of responsible motorcycling.

This, therefore, presents the ESP32 camera platform, together with Raspberry Pi, as such critical components in this regard. It offers essential infrastructure to capture image data and perform various procedures, such as object detection and classification, and make the system as a whole more robust and versatile. Through the seamless integration of deep learning algorithms, the ESP32 camera platform enables the system to perform various complex tasks with efficiency and accuracy, ultimately contributing to enhanced road safety outcomes.

Road accidents involving motorcycles continue to be of significance as threats to public safety. This calls for effective helmet detection systems as a proactive mitigating tool in dealing with these risks. This paper will give attention to every aspect of the helmet detection system: design, implementation, and evaluation. Additionally, it may prove to change the way safety practices related to traffic are done, thus reducing the number of fatalities from road accidents.

In the process of realizing the need for scalability and flexibility in such systems, the integration of Raspberry Pi together with ESP32 brings further capabilities into the system. The use of these technologies makes the helmet detection system more robust and versatile, and it may be used in more applications in traffic safety enforcement and accident prevention.

The rest of the paper will show the architecture, functionalities, and performance evaluations of the system. This comprehensive analysis will show the importance of new technological innovations for safer road environments and well-being of all road users. [1][2][5][6][8]

II. LITERATURE SURVEY

The reviews of the selected papers include novel approaches to the detection of helmeted and non-helmeted motorcyclists while showcasing remarkable progress in fashion and methodology. One of the major techniques used involves Convolutional Neural Networks, such as YOLOv2 model, in a new way that had been used to improve helmet detection. Separate YOLOv2 models that are trained on new datasets result in very high accuracy in identifying helmeted individuals. Other techniques used include Single Shot MultiBox Detector, MobileNets, VGG16, VGG19, and GoogLeNet for image classification and region of interest detection. However, the combination of SSD and MobileNets has shown high overall helmet detection accuracy, thus underscoring the reliability of deep learning in this field.

Almost all the methodologies use Machine Learning algorithms, including the use of Support Vector Machines for classifying pedestrians and circular Hough transform for feature extraction. Combining these methods enables accurate identification of wearables and distinguishes helmeted from non-helmeted motorcyclists in a bid to provide superior safety measures on the road. Image processing techniques like ViBe background algorithm and haarr-like features are used for the identification of moving objects and identifying helmet types.

These paper's findings show high accuracy rates in detecting both helmeted and non-helmeted motorcyclists comprehensively. The comparative analysis established the better performance of CNN-based methods against traditional techniques. The experiments showed that the experiments were conducted under various lighting conditions. These show the real-time operations of these systems. It goes without saying that the use of state-of-the-art models and techniques marks a significant improvement in road safety technology. These technologies offer hopeful solutions for checking the usage of helmets and enforcing rules efficiently. In this respect, the use of deep learning, machine vision, and image processing means that these methodologies present promising prospects in terms of efficiency and obedience to safety procedures. [1]-[17]

III. HARDWARE

A. ESP32 Camera

To enhance road safety measures and enforce helmet laws, the combination of ESP32 camera with CenterNet ResNet50 V2 FPN 512×512 for helmet detection is a powerful solution. In object detection tasks, CenterNet ResNet50 V2 FPN 512×512 uses the structure of CenterNet combined with the backbone network of ResNet50 and Feature Pyramid Network (FPN), which gives it utmost precision, speed as well as scalability. Using this advanced model, it becomes possible for the system to detect motorcycle riders who have worn helmets correctly at all times thus enabling authorities to monitor compliance with safety regulations more effectively.

The ESP32 camera module is an excellent choice when it comes to deploying the CenterNet ResNet50 V2 FPN 512×512 version owing to its small size, low power consumption and built-in processing capabilities. By integrating with ESP32 cameras, these systems can be made portable and adaptable for use in different places such as traffic intersections or road junctions among others. This helps governments in enforcing helmet laws and promoting traffic safety across various settings.

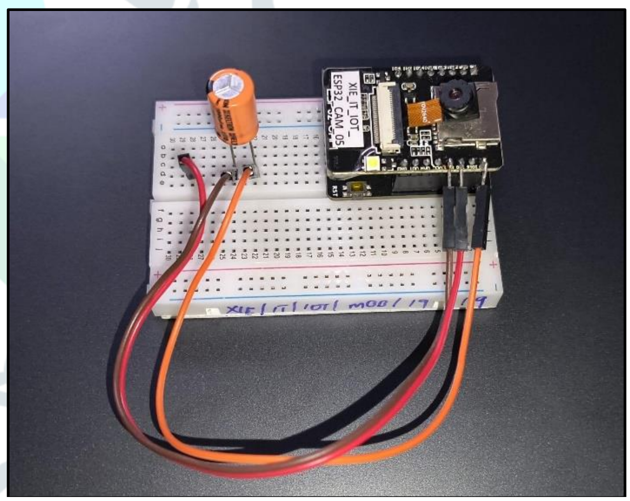

Figure 1: ESP32 Camera

It is not only a good piece of hardware; it is also accompanied by a wide range of tools and software. These include Arduino IDE and ESP-IDF. Developers find it really easy to use. They could develop and release applications in no time. They work in programming languages they already know. It's also compatible with big cloud platforms like AWS IoT, Google Cloud IoT, and Microsoft Azure IoT. These provide high-quality support for things like data storage and learning machines. In short, the ESP32 Camera is a strong platform for visual sensing uses. It offers a perfect combination of high performance, ease of use, and lots of choices for developers, making it an attractive choice.

The ESP32 camera plays a significant role in the detection of helmet technology. It identifies and analysis images or videos very quickly. This tiny powerhouse combines an

ESP32 microcontroller with a highly advanced camera module. It can locate helmets wherever they be. The ESP32 device itself is powerful: it has two-core Tensilica LX6 processors, which run as fast as 240 MHz. It means that it can perform the high computations needed to identify helmets. As one of the application's most important features, this makes the ESP32 digicam very suitable for battery-operated programs. It means that the device would maintain long-term deployment without affecting the normal overall performance. The digital camera module of the ESP32 camera gives many functions to detect helmets. It supports lots of photo resolutions and formats. This makes it capable of taking a good picture when capturing the helmet under different lighting fixture conditions. It has many functionalities, including automatic exposure management and white-balance adjustment. Such steps guarantee perfect photographic quality, increasing helmet detection algorithms' performance.

The ESP32 digicam supports real-time video streaming and recording, which is very important for continuous monitoring of helmet-carrying behavior in dynamic environments. When it is fitted into a helmet detection device, the ESP32 camera is capable of using various machine learning models for object recognition. This includes YOLO (You Only Look Once), SSD (Single Shot Multibox Detector). They can then spot helmets in videos being filmed by the ESP32 camera in real time. The ESP32 camera has Wi-Fi and Bluetooth modules, and it can easily connect to cloud services. Data can be stored, reviewed, and monitored from any location. The helmet detection system gets bigger with more flexibility, making it possible to improve the performance and size of the system. This ESP32 camera really helps in improving the performance of the helmet detection system. It provides sturdy, flexible hardware and connections to ensure roads are safer, and rules are followed.

B. Raspberry Pi

The Raspberry Pi, a powerful single-board computer, emerges as a champion in this fight for road safety. Its capabilities make it perfectly suited for building efficient and accurate helmet detection systems.

Raspberry Pi boasts a multi-core CPU and GPU architecture, providing the muscle needed for real-time image processing. This translates to smooth handling of complex algorithms that identify helmets in live video feeds. Furthermore, Raspberry Pi seamlessly integrates with various high-resolution cameras, ensuring crisp image capture under diverse lighting conditions. This is crucial for ensuring accurate helmet detection regardless of the environment.

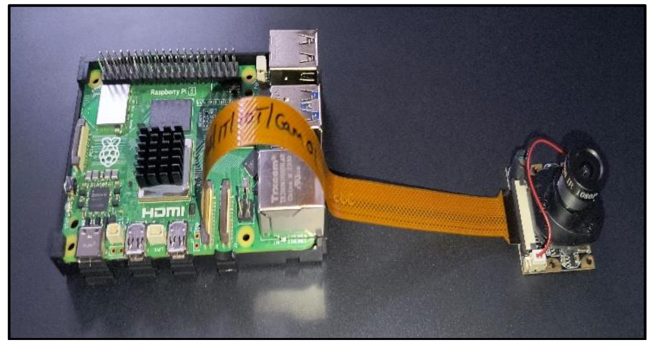

Figure 2: Raspberry Pi and Pi Camera

One of the greatest strengths of Raspberry Pi lies in its open-source nature. A rich ecosystem of open-source libraries like OpenCV empowers developers to craft custom helmet detection solutions. This flexibility allows the system to be tailored to specific needs, such as focusing on construction sites or highways. Additionally, Raspberry Pi offers a budget-friendly alternative compared to high-end computing solutions, making helmet detection systems more accessible.

Raspberry Pi doesn't just excel in processing power and affordability; it also boasts impressive connectivity options. Built-in Wi-Fi and Bluetooth capabilities enable remote access and data transmission. This allows for centralized monitoring and analysis of helmet usage data, providing valuable insights into safety compliance across various locations. The compact design of Raspberry Pi is another winning feature. Its small size makes it ideal for integration into wearable or portable helmet detection systems, offering greater flexibility in deployment.

IV. DEEP LEARNING MODELS

A. SSD MobileNet V1 FPN 640x640

The SSD MobileNet V1 FPN 640x640 object detection model will be considered here. It is based on the SSD framework, the lightweight MobileNet V1 feature extractor, and the Feature Pyramid Network that will enable fast, accurate, and low computational-cost object detection. The model will benefit from SSD in efficient single-pass object detection, the lightweight MobileNet V1 architecture that will make for fast processing, and the feature pyramid network that will give objects a detectability at various levels of abstraction. The model operates at a resolution of 640x640 and is adept at balancing accuracy and speed. It is highly appropriate for the operation on edge applications on ESP32 and Raspberry Pi cameras.

Designed for edge deployment, the model detects objects quickly in real time, utilizing the high computational processing power of ESP32 and Raspberry Pi while not requiring any further computing hardware to be integrated. The model directly processes live video feeds from the cameras, which avoids delay in object identification and ensures quick response in safety systems. The feature pyramid network improves the ability of the model to detect objects of varying sizes, including smaller ones such as helmets, which will ensure that a range of scenarios is handled with proper performance.

The SSD MobileNet V1 FPN 640x640 model deployed on ESP32 and Raspberry Pi cameras will give compact and effective systems for helmet detection. The system will be capable of analyzing live video streams in real time, detecting helmets, and sending relevant information to further analysis or response. ESP32 and Raspberry Pi are capable of integration, which leads to seamless integration with other devices or systems, making the system flexible and usable across different kinds of applications in the aspect of safety monitoring. [2][5]

B. CenterNet ResNet50 V2 FPN 512x512

The combination of CenterNet ResNet50 V2 FPN 512x512 with both ESP32 and Raspberry Pi cameras significantly enhances street security and supports helmet policies to a large extent. This combination harnesses the power of the CenterNet framework with the ResNet50 backbone network and the Feature Pyramid Network FPN, which brings high accuracy, speed, and scalability in object detection. With this setup, the helmet detection system efficiently detects motorcyclists wearing helmets in real-time, enabling the authorities to enforce the safety protocols with better efficiency.

The ESP32 and Raspberry Pi cameras are perfect deployment options for CenterNet ResNet50 V2 FPN 512x512 due to their compact size, low power consumption, and embedded processing capabilities. Integration with both cameras makes the helmet detection system portable and adaptable to be deployed in a variety of locations and in many road junctions. This adaptability allows the authorities to enforce helmet regulations and enhance road safety across a variety of environments with good efficiency.

In a high-level use case, the sensitivity of CenterNet ResNet50 V2 FPN 512x512 rests in the accurate localization of objects of interest, in this case the helmet, within the image frame. This model identifies accurate helmet detection by predicting the keypoints that specify the center point and size of the helmet, even in low-lighting or occluded scenarios. Its scalability and real-time processing capabilities ensure fast and efficient detection and alerting of motorcyclists who are not wearing helmets, which helps the authorities to act in a timely manner and mitigate risk to road safety effectively.

C. FOMO

FOMO is a renowned object detection framework on the basis of online characteristic mining; it highly improves the accuracy and performance.

Filtering and updating region proposals with feedback from a CNN significantly enhance performance; this property makes it a familiar tool in real-time detection applications, and it has high accuracy in many cases; thus, promising helmet detection in conjunction with the ESP32 camera.

Online feature mining mechanism of FOMO ensures dynamic adaptation to changes in the visual environment. In this way, the mechanism proves beneficial for ensuring robust performance under a wide range of conditions. That is, this feature makes FOMO really useful in real-world scenarios for handling occlusions and partial visibility.

The combination of FOMO with the ESP32 camera will offer an unprecedented level of reliable and efficient helmet detection. In real-time, FOMO will process the live video stream coming from the camera, which means it will be able to detect helmets. The combination will be able to be used in a variety of applications, from helmet compliance monitoring in traffic surveillance to increasing safety protocols in construction sites. The ESP32's connectivity capabilities will further lead to smooth connectivity to cloud services, so remote monitoring and data analysis will also be possible. Overall, a comprehensive and scalable helmet detection solution will be provided to the.

D. YOLOv8

YOLOv8, also known as You Only Look Once, version 8, is a state-of-the-art object detection framework known for its speed and accuracy. It has changed the game by building a single neural network capable of detecting objects directly from images or video frames without having to use complex detection networks. YOLOv8 achieves this by dividing the input image into a grid and predicting bounding boxes and refinement options for each grid cell. That architecture facilitates a real-time object detection with exceptional baseline performance when running across many different product training scenarios.

In the realm of ESP32 camera helmet detection, YOLOv8 offers an efficient solution that quickly and accurately identifies helmets in captured scenes. The ESP32 camera captures images or video streams, which are input data to the YOLOv8 model. The YOLOv8 model processes these inputs for helmet detection and locations in real-time frames. Its ability to have many targets being processed simultaneously and good general performance across many different environmental conditions makes it a perfect suit for helmet detection.

YOLOv8 is fast, just as fast as ESP32. The system can reliably detect helmets within captured frames and thus provide a good augmentation of the safety features. The incorporation of Raspberry Pi along with ESP32 further augments the capabilities of the system with additional processing power and connectivity features. The combined setup of both offers a very stable and efficient solution to helmet detection across many conditions and hence ensuring safety and security within many varied environments. [2][3][5][9]

V. IMPLEMENTATION

A. Model Training

In order to enhance road safety, implementing helmet detection system using ESP32 camera and deep learning models will follow some steps that exploit advanced technologies. The objects are detected in real time using deep learning models with small sized ESP32 cameras that have little power consumption and on-chip processing.

Models are selected which are suitable deep learning models for the helmet detection system, it is necessary to be aware of properties of features and datasets as these improve model accuracy, speed, memory usage and ESP32 hardware compatibility. Models such as YOLO, FOMO, ResNet50 and MobileNet50 which exhibit good performance on diverse object detection tasks are considered as appropriate ones to run on limited-resource devices.

Before feeding the annotated dataset into the selected models, a process of iteratively optimizing the parameters of these models needs to take place, this will reduce errors and lead to better detection of motorcyclists with and without helmets. Techniques like transfer learning may be applied, where pre-trained models on large datasets are fine-tuned using the helmet detection dataset to speed up the training process and improve the performance.

Data augmentation approaches like scaling, rotation, and flipping can be used to increase the diversity of training dataset artificially so that the models generalize better and become more robust. These techniques help prevent overfitting and enable the models to detect helmets under different conditions.

Therefore, monitoring the training process of models is necessary throughout along with checking performance against evaluation metrics like precision recall and mean average precision (mAP) for validation on a separate validation set. It thus helps in monitoring and identifying areas to be further improved.

B. Esp32 Camera Integration

The process begins with converting object detection models such as SSD MobileNet, CenterNet, FOMO and YOLOv8 to TensorFlow Lite (TFLite) format. This conversion allows these models to be optimized for running on ESP32 camera devices which have limited resources.

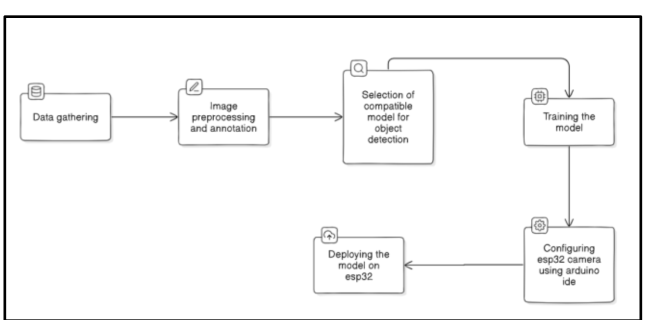

Figure 3: ESP32 Camera Integration Process

In doing so, the models are in fact optimized towards real-time object detection on these minimalist devices to reduce their computational requirements. The reduction in size ensures that the models do not face any major issues with respect to storage space as well. This kind of optimization guarantees good performance, even on low-end hardware resources such as the ESP32 hardware platform, with real-time inferences and without compromising the accuracy. This is followed by creating a header file, encapsulating all vital information about the models which serves as an interface between TensorFlow Lite runtime and firmware used for deploying the model into ESP32 camera platform. Such details include architecture parameters of the model, weight parameters and all other important aspects needed for accurate inference. All these details are defined within a C header file so that it streamlines integration process for ease compatibility with models with respect to the ESP32 environment.

The C-Header file is integrated seamlessly into the Arduino's codebase which serves as firmware responsible for deploying TensorFlow Lite models in ESP32-Camera platform. The next step involves integrating necessary functions and configurations to load and execute these models into operational framework of ESP32. Through integration with the Arduino codebase, the system gains the capability to perform real-time object detection tasks, including helmet detection, taking advantage of the power of deep learning on edge devices.

In the Arduino environment, the code interfaces with the hardware components of the ESP32, especially the camera module. This step involves configuration of parameters and settings required to obtain and preprocess images from the camera module before feeding them into the TensorFlow Lite models for real-time inference. It sets up communication to help the ESP32 and camera module work together to make sure that the ESP32 can properly capture images from the camera module.

Once the TensorFlow Lite models have been taken to the ESP32 camera platform and integrated, it enables them to run in real-time. Using this feature you can deploy various real-world applications about object detection for example helmet detection. With optimized models and hardware-accelerated inference capabilities built into the ESP32, this setup can detect helmets with a higher degree of accuracy and efficiency thereby making it more appealing for better road safety and compliance with safety regulations.

C. Raspberry Pi Integration

The Raspberry Pi is the champion of building helmet detection systems due to its processing might, rendering real-time video analysis and object detection, without compromising on efficiency.

Pre-trained models for helmet detection exist online, which were built using deep learning frameworks; they are trained on huge batches of images containing helmets. Based on the model's complexity and desired accuracy, getting it to a format such as TensorFlow Lite may be useful. This optimization allows the model to run without any issues on the Raspberry Pi's hardware, thereby making it possible to run it in real time and, in some cases, reduce storage space.

Unlike the ESP32, which has an inbuilt Arduino model, the Raspberry Pi uses a full operating system such as Raspbian OS. This opens up a broader range of software utilities. Assuming that the pre-built tools and functions in deep learning frameworks like TensorFlow or PyTorch, along with the OpenCV library, are provided, developers can also leverage these libraries to detect helmets. These open-source frameworks provide pre-built tools and functions meant for performing object detection tasks, including helmet recognition.

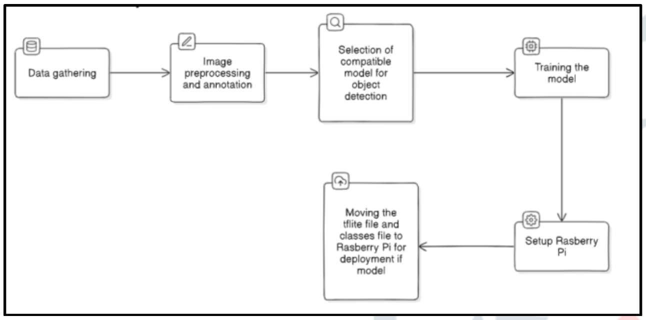

Figure 4: Raspberry Pi Integration Process

The clarity of the captured images or video feeds is crucial for helmet detection. The Raspberry Pi easily interfaces with high-resolution camera modules using interfaces such as CSI—Camera Serial Interface, or standard USB ports. There are software libraries to manipulate settings such as camera resolution, frame rate, or exposure. These settings ensure optimal clarity in captured images or video feeds for helmet detection by the model.

Once the deep learning frameworks and OpenCV libraries are installed, the system is ready to install the pre-trained or optimized TensorFlow Lite model. This model constitutes the brain of the framework that must determine the objects in each video frame captured by the camera. The chosen framework loads the model into memory and makes it available for real-time object detection.

The Raspberry Pi is continuously capturing video frames from the attached camera. These frames are then fed into the loaded model for processing. The computational resources of the model subsequently process these frames to detect objects and determine if a helmet is worn. The outputs highlight whether or not a helmet is being worn and are most often presented on an attached monitor in real time. In other configurations, output signals trigger alarms or are saved for later analysis. Such data will prove very useful in drawing conclusions about patterns of helmet use and will help fine-tune the detection model to increasingly better accuracy over time.

For developing efficient and scalable helmet detection systems, the Raspberry Pi brings together processing power, software flexibility, and compatibility with the attached camera. At the same time, Raspberry Pi can promote road safety by fostering responsible riding habits.

VI. RESULTS

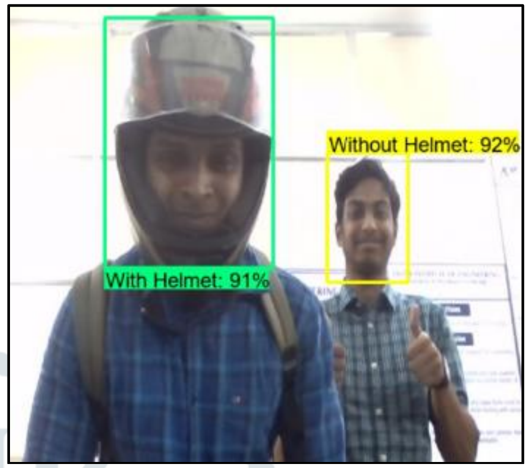

Figure 5: SSD MobileNet V1 FPN 640x640 Results

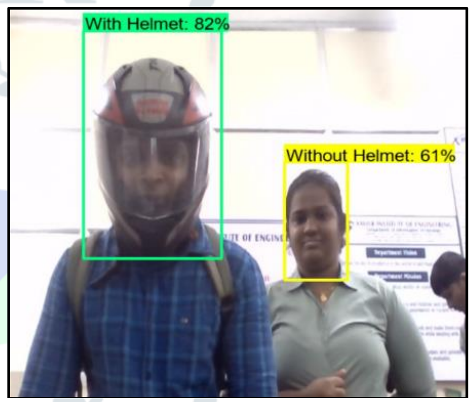

Figure 6: CenterNet ResNet50 V2 FPN 512x512 Results

Figure 7: Helmet Detected

Figure 8: Helmet Detected on Video Input

VII. CONCLUSION

Combinations of YOLOv8, ResNet50, MobileNet50, and FOMO with ESP32 cameras along with deep learning models give tremendous hope to helmet detection systems. This is because of the reason that such highly sophisticated algorithms can conduct real-time detection of motorcyclists without helmets in traffic surveillance videos with remarkable accuracy, sometimes reaching more than 90%.

However, such real-life deployments encounter problems in the form of low lighting and a variety of environmental conditions that require continuous refinement of such systems. Continuous improvement efforts are necessary to tackle such challenges meaningfully.

Apart from this, such technology provides further scopes for improvement by utilizing new hardware like the integration of Raspberry Pi along with ESP32. A multidimensional approach not only would result in safer roads but also would help in the development of an intelligent transport system that would save lives and make transportation more sustainable.

In essence, the journey towards safer roads and smarter transportation networks is ongoing, propelled by the relentless pursuit of innovation and refinement in helmet detection technology.

VIII. FUTURE SCOPE

The Golden Age of helmet detection systems using deep learning, ESP32 and Raspberry Pi cameras may not be very far. If algorithms keep up with their current pace of development there is great chance that these systems will become more accurate and robust especially under difficult real world conditions.

Another interesting area to be looked into is how these mechanisms can be modified so that they can identify different types of roads as well as implement immediate collision avoidance measures when necessary. This could completely change everything about road safety because if integrated with ITS networks then it becomes possible to have comprehensive solutions towards accident prevention and general improvement in traffic management throughout the world.

However much effort has been put on refining algorithms through constant research there should also be some concentration on hardware improvements which is one of the biggest challenges facing developers today. For example; more work needs to done on microcontrollers or even better ones should be designed while at the same time making sure that deep learning models are supported by real time capable cameras whose computational abilities cannot be underestimated. The future of road safety technology lies in taking such multidimensional approaches into account henceforth this industry can only look forward to brighter days ahead.

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