PHONE PATROL: SMART PHONE MONITORING SYSTEM FOR A MOBILE – FREE ZONE

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Abstract— Use of mobile phones in restricted areas like examination rooms, offices and even institutional premises has become a general issue and it may influence discipline, security and good underlined conduct. Majority of the current options that can be applied to manage this problem are based on manual observation or signal-based classification of the problem. Nevertheless, these solutions cannot work in case of airplane mode used or when no network is connected to the mobile phone. This project proposes a real-time mobile phone detection system based on a computer vision and deep learning as a solution to this issue. Through the system proposed, a yearly camera output is used to identify persons and mobile phones using the YOLOv5 object detection model. Only when a person and a mobile phone are spotted in the same frame, a violation is identified and, therefore, it contributes to minimizing false detainments. An alert is sent to alert a body in case of a violation. The system is also deployed on Raspberry PI 5, which is compact, inexpensive, and can be deployed on edges. There is experimental evidence that the system is capable of operating during real-time and giving good detecting accuracy.

Index Terms— Object Detection, Mobile Phone Usage Detection, YOLOv5, Computer Vision, Edge Computing, Raspberry Pi.

I. INTRODUCTION

The use of mobile phones has grown very fast in recent years making them an inseparable appendage in the daily activities. They are popularly applied in communication, learning and in acquisition of information. At some locations nevertheless like in examination centers, colleges, hospitals and government offices among other areas, mobile phone usage is highly restricted.

Mobile phones can also be abused to cheat or even leak confidential information in examination centers and secure places of work, and this will compromise the integrity and effectiveness of the system. In the work office and classrooms, the high usage of the mobile phone disturbs people and makes them less focused hence less productive. In sensitive places like hospitals and laboratories, cellular phones can disrupt electronic/medical devices and this is risky. The issues raise the necessity of a powerful mechanism to regulate and check the use of mobile phones.

Most of these mobile phone detection systems are still traditional and mostly rely on signal or radio frequency detection, which have been used in various years. But all this cannot work under every circumstance particularly where mobile phones have been placed on airplane mode or where there is no network connection.

The solution here is found within computer vision and deep learning approaches, to counter such limitations. Vision-based systems work on images or video streams to identify mobile phone use without necessarily relying on the network communications. The new theoretical progress in deep learning based object detection has demonstrated high accuracy and ability to conduct their processes in real-time and are consequently applicable to monitoring applications. One of such methods, the You Only Look Once (YOLO) algorithm, becomes one of the most popular approaches as it allows matching many objects in one image and does not require any repetitions.

It is the approach adopted by the proposed system to detect a desired reduction of false detections in the system; this involves authentication of the violation only after a visual identification of the mobile phone usage. The alert system is also embedded which can be used to provide real-time alerts whenever there is violation. It is being implemented on a Raspberry Pi 5, which is a relatively inexpensive and self-contained system. In sum, overall the suggested scheme is a viable, dependable, and network insensitive scheme of instigating no-mobile policies in sensitive and limited regions.

II. RELATED WORK

Nowadays, a vast number of researchers engage in the issue of identifying mobile phone use in restricted zones. Previously the methods predominantly relied on the hardware based as well as signal based methods. The approaches identify mobile phones by sensing some radio frequency or electromagnetic waves generated by active devices. Although these methods work in simple cases, they cannot work in airplane mode, silent mode, or when the phones are not connected to a network. Also, signal-based systems are the easiest to be disturbed by the environmental noise and signal shielding and therefore they cannot be used in secure environment.

Other works have suggested a simple circuit-based mobile phone detector due to its cheap nature as well as simplicity in its design. Nevertheless, these detectors have a poor detection range, and are not able to distinguish between permitted and prohibited phone use. They do not also give information on whether an individual is actually using phone. Rather, they just tell us that a mobile device exists and this does not help them in practical situations.

Detection based on vision has become a matter of concern with the advancement of artificial intelligence. Such systems utilize camera visions to examine images or videos and find mobile phones without relying on network signals. In recent literature, it has been demonstrated that deep learning-based object detection algorithms, particularly convolutional neural networks can recognize mobile phones even in busy environments with high accuracy. The vision-based approaches are more effective and flexible as contrasted to the traditional approaches.

The practicality of such systems has also been increased by the use of edge computing devices which include the Raspberry Pi. Raspberry Pi is a popular board due to its low cost, size and power efficiency. Various researchers have demonstrated that light deep learning models are capable of operating on these devices effectively and allow them to perform real-time detection without a cloud. This lessens the time wasted and enables 24 hours monitoring in isolated areas. However, several of the currently available systems based on vision concentrate on the detection of mobile phones and not the context at hand. This can cause false alarms like in instances where a phone has been left on table or it has been carried without usage. Other systems are necessitating big datasets or other external feeds which complexifies their structure.

To address such problems, the suggested system, real-time person and mobile phone detection, is performed in the YOLOv5 model. When an individual and a cell phone are present in the same video frame, this is a violation that is reported. This also aids in the minimization of false alarms. The implementation is performed on a Raspberry Pi 5, implying that it is a rather cheap and serviceable system that should be deployed to impose no-mobile policies in limited areas.

III. PROPOSED MODEL

The system is designed to detect unauthorized mobile phone usage in areas where mobile phones are strictly not allowed. Instead of depending on network or signal-based methods, the system uses a vision-based approach to identify violations through live video monitoring. It is developed as a compact and standalone setup, which makes it suitable for continuous operation in restricted environments. The complete system is implemented using a Raspberry Pi 5, allowing deployment even in locations with limited computing resources.

The working of the system is based on real-time object detection using the You Only Look Once version 5 (YOLOv5) algorithm. A camera placed in the observed location continuously captures video frames, which are then analyzed by the system. Each frame is checked for the presence of two important objects: a person and a mobile phone. A violation is reported only when both are detected together in the same frame. This approach helps avoid false detections, such as identifying mobile phones that are kept on desks or not actively being used.

To enable quick action, an alert mechanism is integrated into the system. Whenever a violation is detected, the system immediately generates a notification to inform the responsible Personnel or supervisor. This allows timely enforcement of no-mobile rules. Overall, the system is designed to achieve accurate detection with minimal computational load, making it suitable for real-time surveillance applications on low-cost edge devices.

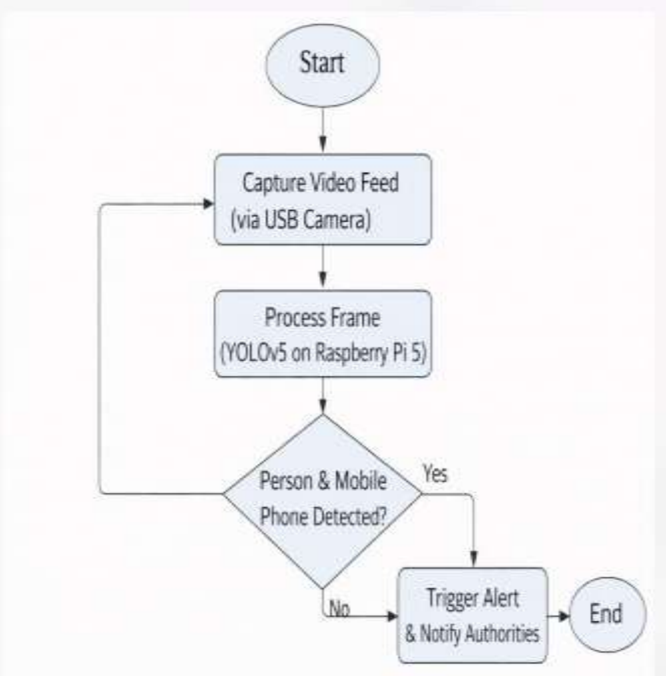

Fig. Proposed System Flowchart.

IV. PERFORMANCE ANALYSIS

This section explains how the proposed system was tested and evaluated. The main purpose of this analysis is to check whether the system can correctly detect mobile phone usage in no-mobile zones during real-time operation. The evaluation is carried out using the experimental setup, dataset details, detection results, and performance metrics.

A. Experimental Setup

The experimental model was developed to test the proposed system on a real time system. The system includes an assembly of Raspberry Pi 5 with a USB camera as depicted in Fig. A. The camera is attached to the surveillance zone and switches to live video all the time.

It relies on the Raspberry Pi 5 as a central processing unit of the system. The entire processing is taken care of on the Raspberry Pi, including image processing and detection of objects. This trained YOLOv5 model had been previously run in a different system and the trained model was consequently transferred to the Raspberry Pi where real- time testing was to be conducted. This deployment will be useful in testing the feasibility of a deep learning model to operate on a low-cost edge device.

In the run of the work, the video stream is broken into frames and each frame is dealt with individually. The model found in the second example is the YOLOv5 designed to detect two items such as an individual and a cell phone. The system treats it as infringement only in a case where an individual and a mobile phone are in the same shot. When the situation is experienced, the system will point out the detection and demonstrate a visual alarm on illegal usage of the mobile phone.

This installation indicates that the proposed system is an independent solution and is not reliant on the internet or the cloud services. The findings of this experiment validate the fact that the system may be practically applied in the regions that are limited.

Fig. A. Experimental setup with Raspberry Pi 5 for real-time mobile phone detection.

B. Dataset

The dataset used for training the mobile phone detection model was collected manually. Images were captured in both indoor and outdoor environments to include different real-world conditions. The dataset contains images of people using mobile phones as well as images where no mobile phone is present.

To make the model more reliable, data augmentation techniques were applied. These include changes in brightness, image rotation, scaling, cropping, and adding noise. Such variations help the model perform better under different lighting and background conditions.

The dataset was divided into training, validation, and testing sets in the ratio of 80%, 10%, and 10%. All images were manually labeled using bounding boxes for class, namely mobile phone.

C. Detection Results

After training, the YOLOv5 model was deployed on the Raspberry Pi 5 for real-time testing. Sample detection outputs are shown in Fig. B. The system draws bounding boxes around detected mobile phones along with confidence values.

Fig. B. Sample output showing mobile phone detection using YOLOv5 in a restricted environment.

The system was able to detect mobile phone usage in different situations, such as changes in lighting, distance from the camera, and user posture. Since the system checks for the presence of both a person and a mobile phone, false detections caused by phones placed on tables or background objects are mostly avoided.

D. Precision–Recall Analysis

Precision–recall analysis was carried out to understand the detection performance of the model. The precision–recall curve is shown in Fig. C. Precision indicates how many detected objects are actually correct, while recall shows how many real objects are detected by the system.

From the curve, it can be observed that the system maintains good precision over a wide range of recall values. This means that most detections are correct and the number of false alerts is limited, which is important for continuous monitoring systems.

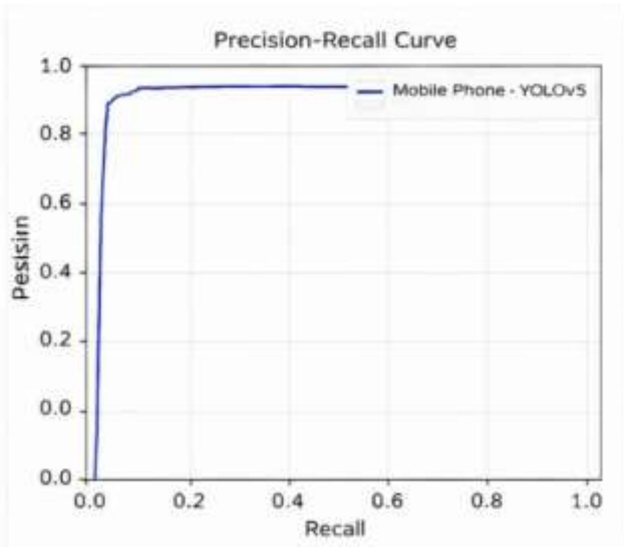

Fig. C. Precision–recall curve for the mobile phone detection model.

E. Performance Metrics

Common metrics, which are used to determine the performance of object detection in the proposed system, including: precision, recall, and mean Average Precision (mAP), were used to assess the performance of the proposed system.

This is because the mobile phone detection model at an IoU threshold of 0.5 had a significant mAP value which implies that mobile phones were detected correctly. The combined precision and the recall values were high as well and this indicates that the system has the potential to identify violations.

On the Raspberry Pi 5, the mean frame time per frame took a range of 200 ms to 300ms. This processing rate is appropriate in near-real time monitoring.

F. Discussion

The experiment results indicate that the vision-based system as suggested is effective in identifying the use of mobile phones in no- mobile area. The YOLOv5 model offers a nice compromise in terms of the accuracy of detection and the speed of processing, even when running on a device with lower computing capabilities such as the Raspberry Pi 5. Despite the fact that the given system works with the specified conditions, there remains a room to be improved. The work of the future can be aimed at making the processing time shorter either with model optimization methods or avoiding frames during detection.

The following are the summaries of the performance analysis that have been conducted.

Overall the performance analysis shows that the proposed system can identify cases of illegitimate cell phone use in real time. The system is fully autonomous without the need to have network connectivity and is capable of giving efficient detection with low latency. Even though the performance can be lower under the conditions of high congestion, the further dataset correction and the model optimization can further increase the system in the next versions.

V. CONCLUSION AND FUTURE WORK

This publication offered a vision-enhanced system of identifying the illegal use of mobile phones in locations that do not permit the usage of mobile phones. In the proposed system, the YOLOv5 object detector model is used to detect moving phones using live video cameras. The system is not mobile network signal reliant as it uses visual analysis. Because of this, the use of mobile phones can still be tracked even when the devices are of airplane or do not have any network.

The whole system was deployed on Raspberry Pi 5, which demonstrates that real-time detection based on deep learning can be realized on a small and inexpensive edge device. As a result of the experiments, it was found out that the system is able to work well under the variety of environments and offers the correct results of the detection. The large detection accuracy of the proposed solution in the course of the testing proves that the proposed solution can be utilized in practice in places like examination halls, hospitals, and secure office spaces. The monitoring control that the system has will assist in acting swiftly whenever a breach has been identified.

In spite of the fact that the existing system is effective, it can be still improved. Pruning or quantization are model optimization strategies that can be utilized in the future to enhance the speed of the processing. Detection accuracy can also be enhanced by increasing the size and diversity of the data by incorporating an increased number of real-life situations. Other functions like identity check, central database, or tracking dashboard can be incorporated to facilitate the mass deployment. Through such improvements, the suggested system can then be refined to a dependable and scalable control over the application of no-mobile policies in sensitive areas.

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