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SMART SAFETY SYSTEM FOR MINERS WITH PPE DETECTION

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ABSTRACT

Mining is one of the most dangerous industries, with risks including toxic gas exposure, severe temperatures, and worker accidents. To ensure worker safety, real-time environmental monitoring is required, as is stringent adherence to personal protective equipment (PPE) requirements. This study combines two safety mechanisms: a Smart Helmet equipped with IoT sensors (DHT11 for temperature and humidity, MQ-2 for gas detection, LM393 IR for object detection, a buzzer for alerts, and ESP8266 for cloud connectivity) and a PPE Detection System that uses computer vision to ensure that workers are wearing necessary protective gear such as helmets, jackets, and gloves. The Smart Helmet continuously monitors ambient conditions, identifying harmful chemicals and aberrant temperatures, and notifies users via a cloud-based system. Simultaneously, the PPE Detection System uses deep learning models like YOLOv5 and OpenCV to examine real-time video streams and determine PPE compliance. This solution improves workplace safety by integrating IoT and AI-based safety measures, lowering accident risks and providing real-time supervision. The proposed approach is tested in simulated situations to demonstrate its effectiveness in enhancing mine safety. Future improvements include increasing PPE detection to encompass more safety equipment and using sophisticated communication protocols for better real-time monitoring.

Keywords: Nodemcu (ESP8266), Mining Industry, Computer Vision In Safety, Occupational Safety, Iot-Based Safety System.

I. INTRODUCTION

The natural conditions of coal mine are very complicated and the production conditions are very transformed. Many disasters can occur in mine, which can lead to a lack of safety of coal production and easily leading to serious accidents, which is very difficult to ensure safety. The structure of the coal mine media is complicated. The space in the branch tunnel is limited and the instructions of the branches are not recorded. The transmission system is often installed only in the main tunnel, so it is greatly limited in the network. [1] It is very important to build an effective recognition system to increase production safety. This can provide an early warning of potential safety and health risks. This system should collect, transmit, and process data on each miner's health state, tiredness levels, ambient gas levels, and accurate position. Some miners appear to abandon the subterranean shaft till the end of their shift. Mining control does not track these early rests, hence the number of miners who fall into the trap is unknown. [3] Thanks to the rapid development of information technology, sound and artificial intelligence, the prospect of intellectual security for the safety of coal mining can lead to the collapse of threatening the life of the miners and complicating rescue work in addition to structural risks associated with underground food. In this environment, the operation of heavy equipment increases the possibility of thinking by increasing the possibility of thinking, as described in various research and security reports. [5] In 2013, the FFH accounted for 36.9% of US producers, 31% in the United Kingdom, and 12% in Australia. In 2019, 50.1% of deaths were caused by the FFH, which was affected by items in all industrial sectors, and a conflict occurred at a Korean construction site (Kim et al., 2020). 41.2% of these deaths were due to head traumas. Despite the fact that most construction workers understand the importance of wearing a protective helmet, over 60% do not do it appropriately or in discomfort, resulting in injuries and deaths. [6] Despite its economic importance, mining remains a dangerous business in terms of personality, putting personnel at risk. Among various types of mining, coal mining is particularly dangerous due to frequent and heavy accidents that occur in this environment. These thinking ranges from the collapse of the roof and the gas explosion, which can result in fatal consequences for both human life and environment. [7] This overall approach recognizes the multi -dimensional characteristics of the problem of underground mine. The international importance of this study is to establish a new standard for decision -making process when choosing a sensor for underground operation for mining. As the mining industry continues to develop, adopting advanced technology is essential and can identify the best sensors that are decisive in preventive safety measures. The results of this study will not only influence the mining community, but also improve security standards, as well as contribute to valuable information in the wider scientific decision -making field where multiple standard methodologies are constantly developing. [8] Head injuries are very dangerous during construction. Leaders can absorb external force and prevent them from penetrating objects, making them an important tool for reducing the frequency of injuries. But according to the Labor Statistics Bureau, 84 % of the head injuries were not on the helmet. [19] In addition, industries such as production, construction, transportation and storage are faced with high indicators of accidents related to work. According to the International Labour Organization (ILO), approximately 2.3 million people die each year as a result of work-related accidents or diseases, which equates to more than 6,000 deaths per day. Around the world, there are approximately 330 million workplace accidents and 160 million people affected by occupational diseases. [9]

Globally, the industrial and construction industries have had some notable expansion in the past ten years. Even though safety has become a top focus, accidents continue to happen there and are sometimes missed until it is too late. No matter how serious the injury is, it can significantly affect the worker, their family, the project's budget, and schedule. As a result, a number of programs have been implemented recently to improve the efficiency and safety of construction sites.[10] Over the years, reports of dangerous site worker behavior and risky AEC project delivery have persisted. The AEC sector is thought to be accountable for one out of every six fatalities, with roughly 2.78 million deaths resulting from occupational accidents.[11] In the United Kingdom, 470,000 workers suffer skeletal illnesses as a result of their jobs, and 142 are reported to have died as a result of occupational hazards. The construction industry, given its operational characteristics, makes a significant contribution to these statistics. With technological advancements, such as the integration of machine vision algorithms and robotics, there is a growing opportunity to raise global workplace safety standards and reduce the human toll of occupational hazards on an international scale.[12] To name a few, PPE can be divided into the following categories based on the specific body part and physiological function they are intended to protect: (1) eye and face protection (e.g., welding masks, safety glasses, face shields, etc.); (2) head protection (hard hats and caps); (3) hearing protection (earmuffs and earplugs); (4) hand and arm protection (gloves); (5) foot and leg protection (steeltoed boots); and (6) respiratory protection (masks) (Occupational Safety and Health Administration 2004; Regulation (EU) 2016/425 2016).[13] Research on automatic recognition of reflective clothing is also very significant since the properties of reflective clothing are very different from those of hard hats, and their variability and overlap make it difficult to detect reflective clothes.[14] Therefore, one of the most crucial duties for safety management is to supervise workers wearing personal protective equipment (PPE). In order to overcome the limited visual area of manual monitoring, researchers have started looking at computer vision techniques to enable automatic supervision.[15] Though wearing personal protective equipment (PPE) significantly reduces risk, there are still issues with PPE recognition and detection in substations. First, the complex and variable working conditions in substations can make PPE detection less effective. [16] Experimental results show that our suggested method performs better than traditional yolo models in terms of detection accuracy, inference speed, and computational efficiency under complex industrial environments, making it suitable for real-world power safety monitoring applications.[17] In order to optimize the use of the virtual domain in the real-world domain, this study explores a domain adaptation method. As a result, an object detection model requires less data in the real world. In particular, using a few real image training examples, we show how the transfer learning approach on a popular deep neural network can be trained with virtually generated images of people wearing safety gear, such as high-visibility jackets and helmets, and domain adaptation to achieve state-of-the-art results in automatic visual media indexing.[18]

II. Proposed Methodology

In order to improve mine worker safety through real-time monitoring and compliance verification, the suggested methodology combines a smart helmet with a computer vision-based PPE detection system. This two-pronged strategy guarantees that personal safety precautions and the workplace are regularly updated. An ESP8266 microcontroller is linked to a number of sensors on the smart helmet. In order to identify environmental discomfort or danger, the DHT11 sensor keeps an eye on temperature and humidity. Hazardous gases like smoke and methane, which are prevalent in mining sites and can cause deadly accidents, are detected by the MQ-2 gas sensor. In order to identify any physical hazard, the LM393 infrared sensor is employed to detect abrupt movements or falls. Additionally, a buzzer is built into the device to instantly notify the worker in the event that any readings are abnormal. Wireless data transmission is made possible by the ESP8266, which transmits sensor information in real time to a centralized monitoring platform. This enables managers to keep an eye on several employees at once and respond quickly when important benchmarks are reached. The system is made to log environmental conditions for safety audits and to provide real-time alerts. A PPE detection system is being built in parallel with the smart helmet utilizing Python and computer vision frameworks like TensorFlow and OpenCV. The technology examines surveillance camera video feeds to determine whether employees are donning gloves, jackets, and helmets, among other necessary safety equipment. An object detection model, like YOLO, is trained using a dataset of annotated photos of workers wearing and not wearing personal protective equipment. This model detects personal protective equipment (PPE) in live video frames and highlights any missing gear. The monitoring system receives alerts from the model to make sure that only workers with the appropriate gear are permitted in dangerous areas. The suggested method offers a thorough, two-layer safety framework by combining the two technologies. The vision system guarantees PPE compliance, and the smart helmet continuously monitors physical and environmental parameters. When combined, they provide data to a single dashboard for real-time monitoring, facilitating enhanced safety procedure enforcement and quicker emergency response. By combining IoT and AI technologies into a single system, this method improves the general safety of mining operations.

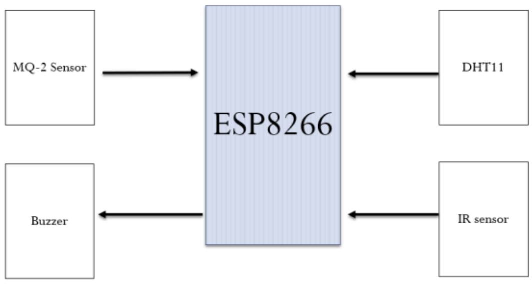

Fig.1 Block Diagram

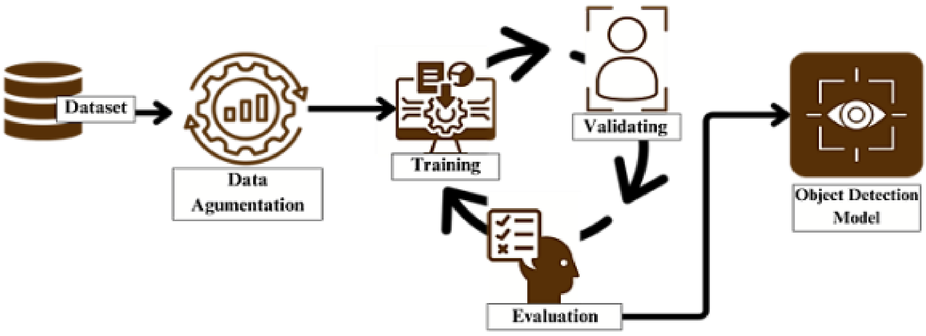

Fig.2 Methodology behind object Detection

II. CIRCUIT DIAGRAM

The connections between the ESP8266 (NodeMCU) microcontroller and other sensors needed to monitor environmental conditions and worker safety are shown in the smart helmet system's circuit diagram. The system incorporates a battery-operated DHT11 temperature and humidity sensor, a MQ-2 gas sensor, an LM393 infrared sensor, and a buzzer.

Temperature and humidity conditions in the mining environment are measured by the DHT11 sensor. For continuous temperature and humidity monitoring, it contains three pins: VCC, GND, and Data. The VCC pin is connected to the 3.3V/5V pin of the ESP8266, the GND pin is connected to the ground (GND), and the Data pin is connected to one of the GPIO pins of the ESP8266.

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Hazardous gases like smoke, carbon monoxide, propane, and methane can be detected using the MQ-2 gas sensor. It has an analog output (A0), VCC, and GND. To transmit gas concentration data to the microcontroller, the A0 pin is connected to an analog GPIO pin, the VCC is connected to the ESP8266's 3.3V/5V pin, and GND is connected to ground. An alert is set off if the gas levels rise above a safe level.

To detect falls, the LM393 infrared sensor is employed. It uses infrared photons and reflection measurements to detect motion. In order to detect abrupt falls or unusual worker movements, this sensor is powered by 3.3V/5V from the ESP8266 and has its output pin attached to a digital GPIO pin. The system has a buzzer to give quick warnings in the event of dangerous situations. When activated, it makes a loud noise to alert the worker and other nearby staff. It is attached to one of the ESP8266's GPIO pins.

The ESP8266 and all other linked components are powered by a battery source that powers the complete circuit. As the central processing unit, the ESP8266 gathers, processes, and sends data from the sensors to a cloud server or monitoring dashboard via its included Wi-Fi module. The technology ensures prompt interventions by generating alerts if any parameter surpasses safety limits.

In order to improve worker protection in dangerous mining conditions, this circuit design successfully incorporates IoT-based real-time monitoring and safety alarm methods. A strong and dependable safety system is ensured by combining sensor-based environmental surveillance with cloud-based data transfer.

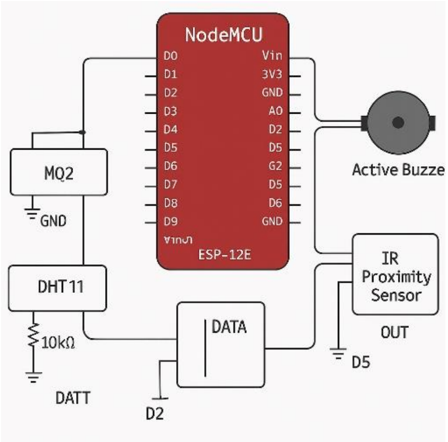

Fig.3 Circuit Diagram for Smart Helmet

III. PROPOSED ALGORITHM

An algorithm for continuous sensing and decision-making powers the smart helmet system. The DHT11, MQ-2, and LM393 infrared sensors are among the sensors that the ESP8266 initializes when it is powered on. After that, the system goes into a loop where it reads data from the MQ-2 to identify the presence of dangerous gasses, the DHT11 to track temperature and humidity, and the LM393 IR sensor to track abrupt movements or falls. The gathered information is contrasted with predetermined safety thresholds. The device promptly alerts the worker by sounding the buzzer if any parameter—like a high temperature, a toxic gas concentration, or a fall detection—exceeds safe limits. In order to provide centralized logging and real-time supervision, the data is simultaneously transmitted over Wi-Fi to a cloud server or monitoring dashboard. This loop continues at short intervals, ensuring ongoing safety monitoring.

The technique used by the PPE detection system is based on object detection and image processing. Video frames are first taken from a live camera feed that keeps an eye on the mining area. Preprocessing involves resizing, normalizing, and running each frame through an object identification model, such YOLOv5 or MobileNet SSD, which has been taught to identify particular PPE items, such as gloves, safety jackets, and helmets. The model looks for these objects on each person and recognizes and categorizes them within the frame. The system detects that frame and generates an alert indicating non-compliance if any of the necessary PPE components are absent. The safety officer can then view this data and take the appropriate action when it has been sent to the monitoring dashboard. When workers enter or travel through the hazardous area, the system's real-time operation guarantees ongoing PPE usage verification.

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When combined, these algorithms allow real-time sensing and visual verification to be seamlessly integrated, creating a strong, intelligent safety framework for mining situations.

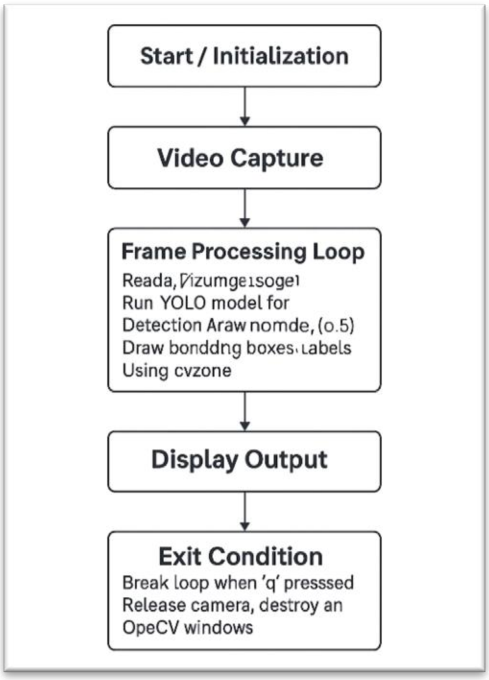

Fig.4 Algorithm used for Object Detection

IV. RESULT

The smart helmet system's successful deployment allowed for real-time environmental condition monitoring in mining sites. Accurate data on temperature, humidity, gas levels, and fall detection was recorded and sent to the cloud, causing buzzer alarms to sound when dangerous conditions were present. At the same time, the Python-based PPE detection model used object detection techniques to reliably identify gloves, jackets, and helmets in live video feeds. By efficiently flagging instances of non-compliance, the system made sure that only personnel with the appropriate gear entered dangerous areas. By combining automation and real-time data analytics, the integrated solution showed increased worker safety, quicker emergency response, and improved safety procedure enforcement.

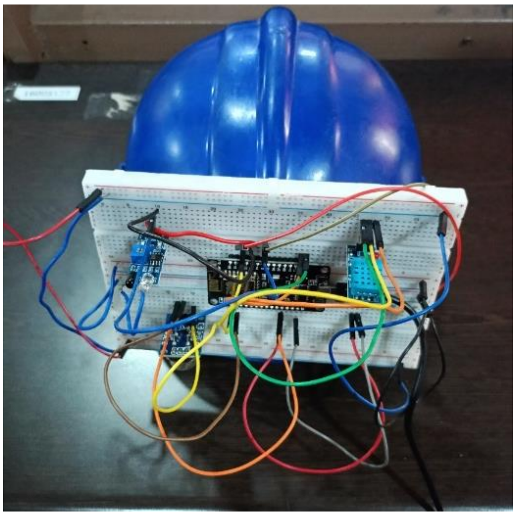

Fig.5 Photo of Smart Helmet

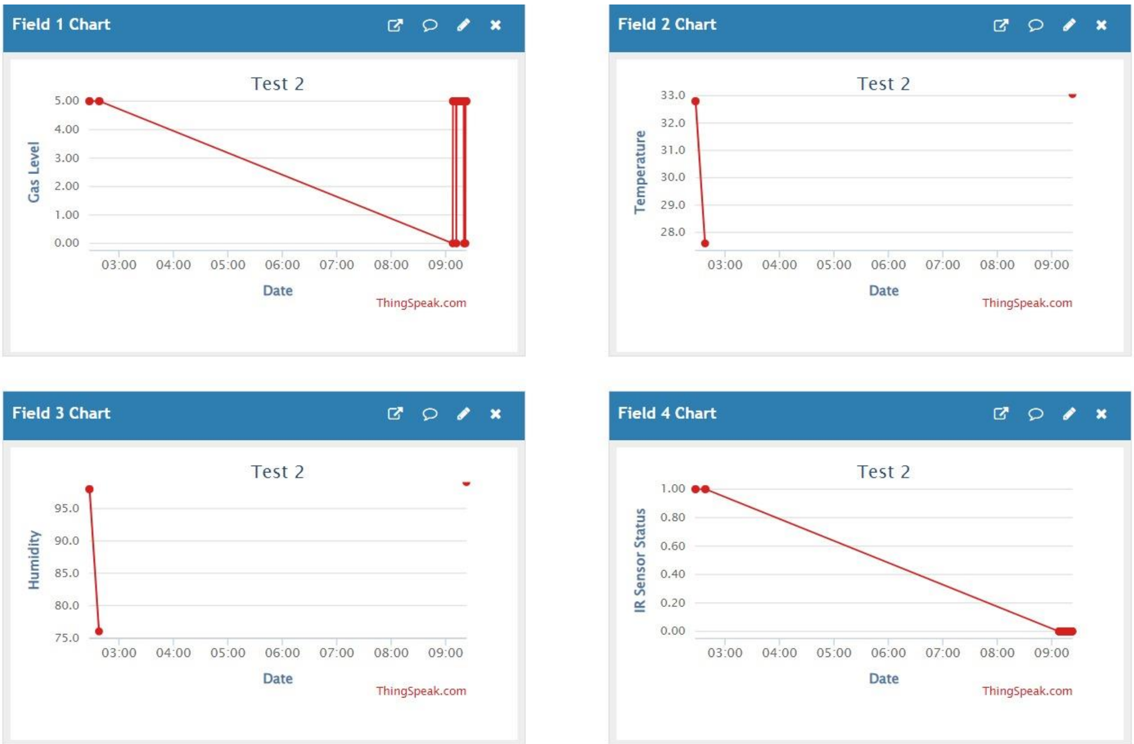

Fig.6 ThingSpeak results

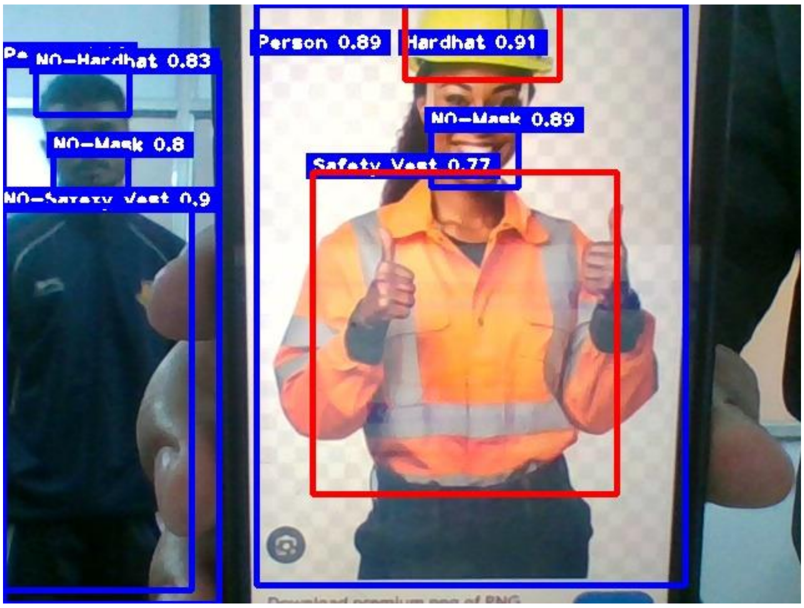

Fig.7 PPE kit Detection using YOLO

V. CONCLUSION

The combination of the computer vision-based PPE detection system and smart helmet offers a thorough and efficient method of improving mine worker safety. The technology tackles two crucial facets of workplace safety hazard detection and personal protection enforcement by fusing automated safety gear compliance checks with real-time environmental monitoring. While the PPE detection model makes sure that employees have the necessary protective gear before entering high-risk areas, the smart helmet effectively monitors temperature, humidity, hazardous gasses, and fall accidents. In addition to speeding up emergency response times, this two-pronged approach encourages a culture of safety and responsibility in mining settings.

VI. FUTURE SCOPE

The suggested system has a lot of room to grow and expand in the future. To provide more thorough health and location tracking in the future, the smart helmet can incorporate more sensors like heart rate monitors, GPS modules, and noise level detectors. Advanced deep learning models can be used to increase the PPE detection system's accuracy in a variety of ambient and illumination circumstances. Supervisors and emergency responders can receive real-time warnings and analytics through integration with IoT dashboards and mobile applications. Furthermore, this system's influence on workplace safety can be expanded by using it in other high-risk sectors like manufacturing, construction, and oil and gas.

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