Proceedings of 7th International Conference on Mechanical, Industrial and Energy Engineering-Part II
22-24 December, 2022, Khulna, BANGLADESH
SciEn Conference Series: Engineering Vol. 2, 2025, pp 1-4 https://doi.org/10.38032/scse.2025.2.1

An Intelligent Industrial Safety and Health Monitoring System for Industry 4.0

Prangon Das[1,*], *Sarafat Hussain Abhi*[1], *F.I.Z. Suhreed*[1], *Jalal Uddin*[1], *Shahriar Jahan*[1], *Roknuz Zaman*[1], *Md. Abul Kashem*[1]
[1] Department of Mechatronics Engineering, Rajshahi University of Engineering & Technology, Rajshahi-6204, Bangladesh

ABSTRACT
Due to the depletion of Diesel fuel and higher cost, it is desirable to find alternative fuel with lower cost and better combustion and emission characteristics. As, gaseous fuel is cheaper than liquid fuel, one of the effective solutions to obtain better engine performance is replacing a portion of liquid fuel by gaseous fuel in CI engine which is called dual fuel CI engine. In dual fuel engine, main gaseous fuel is provided through intake manifold by premixing with air and the mixture is ignited by injecting liquid pilot fuel at near the end of the compression stroke. The process is cost effective as well as the engine obtain higher thermal efficiency and lower soot, CO, UHC emission. But NOx emission is increased in CI engine with dual fuel mode which adversely affected the human health and pollute the environment. By applying Exhaust Gas Recirculation (EGR), NOx emission and knocking of the engine can be reduced. In this numerical simulation, the effect of EGR on combustion and emission performance of dual fuel CI is investigated through ANSYS Forte 18.1. In this study, gasoline is considered as main gaseous fuel and diesel is considered as liquid pilot fuel. Effect of EGR on various engine parameters such as in-cylinder pressure, temperature, heat release rate, ignition delay, combustion duration, NOx, CO and UHC emission is investigated. It is seen that, in-cylinder peak pressure is reduced to 50.65% and in-cylinder maximum temperature is reduced to 60.19% for the addition of 40% EGR. NOx emission is reduced to 57.19% for the addition of 10% EGR, 21.32% for 20% EGR, 1.57% for 30% EGR and 0.014% for 40% EGR.

Keywords: Exhaust Gas Recirculation, Diesel-Gasoline Dual Fuel CI Engine, Combustion and Emission Performance

1. Introduction

The evolve in the field of intelligent industrial safety and environmental health monitoring has come across diverse grandstands. Numerous appliances are integrated to ensure safety in industrial applications. A crucial safety element in the development of safe manufacturing is the adoption of safety helmets by industrial workers. The helmet can lessen the extent to which the heads of laborer collide after falling from a height, counterbalance the force of some objects falling from higher elevations, and even save their lives. The main reason why there are fatalities at some worksites right now is because the workers there didn't carry out their tasks in compliance with the principles developed. Laborers disregard these safety regulations in many real-world settings due to a variety of objective variables, such as hot temperatures and a lack of monitoring, and the phenomena of not wearing protective helmets occurs mainly. A million incidences per year in China also put a great deal of strain on communities and individuals. Available data state that employee lawbreaking accounts for 95% of accidents occurring [1]. In essence, safety mishaps are common on worksites everywhere in the globe. One in five fatal accidents in the private sector occurred in the U.S. construction industry in 2014, the highest rate of casualties across all industries [2].

Moreover, due to the rise of the COVID-19 pandemic, wearing face masks also became an emergency for the workers in industries. With COVID-19, superfluous initiatives have been halted or reduced, which has had an impact on the people in those industries. Nevertheless, because they play such an important part in people's lives, many construction activities cannot be put on hold. In order to maintain the logistics system's use, initiatives like bridge maintenance, street widening, highway repair, and other crucial infrastructure improvements have been restarted. Despite the activation of building projects, the security of laborer cannot be disregarded. There is a significant risk of contamination spreading on work sites because of the high labor population [3].

In the context of environmental purity, clean air is a vital need for the regular process in industrial aspects. Authorities have always addressed this concern to ensure the environmental purity and protection. Safety is impacted by poor air quality, which is seen as a significant overseas issue, particularly in nations with extensive coal and gas sectors. The United States Environmental Protection Agency (US EPA) [4] asserted that monitoring gases can help determine the cleanliness of the air. The fundamental goal of environmental safety monitoring is not only to collect information from various sites, but also to give researchers, engineers, and regulatory the knowledge they need to make policies about how to manage and improve the ecosystem, as well as to facilitate useful data to end-users. There are significant attempts made to enhance the quality of the air both inside industries and outside of the industries.

This research is novel because it uses cutting-edge computational intelligence approaches to provide a coherent framework for measuring workplace safety compliance and lowering the number of casualties and major incidents from accidents among laborer. The model created in the article is an innovative framework that helps the participants to d identify helmet and mask usage on industrial sites and monitoring environmental health monitoring of the industry combined. The tasks are conducted with the utilization of deep learning with intelligent detection capabilities.

The rest of this paper is organized as follows. Section II discusses the related work. Section III introduces the developed system architecture and Section IV describes the proposed method in detail. Section V systematically evaluate the performance of our proposed method. Finally, Section VI concludes**.**

2. Related Work

There is practically little research on helmet wearing recognition. In the fields of machine learning and computer vision, it's a rather emerging discipline. The focus of the research centered on exploiting coloration analysis to detect helmets. Silva et al. [5] extracted visual characteristics using the Circle Hough Transform (CHT) and Histogram of Oriented Gradient (HOG) analyzers, and then classified the target using a multilayer perceptron processor (MLP). This approach is successful for mono detecting; however, it fails miserably at detection with many classes and is inapplicable to multiple-person based photos. For the purpose of detecting helmets in video sequences, Du et al. [6] presented a cumulative evolutionary computation and computer vision technique. They used three main components in their approach: the initial was the user's facial recognition focusing on Har-like facial characteristics [7], the other one was the movement tracking and skin color sensing utilized to cut down on error rates of facial expression, and the third was the helmet identification using the spectral information over the shape features. For helmet detecting for ATM's monitoring technologies, Wen et al. [8] presented a circle identification technique called Modified Hough Transform. However, the methodology is trained on insufficient data.

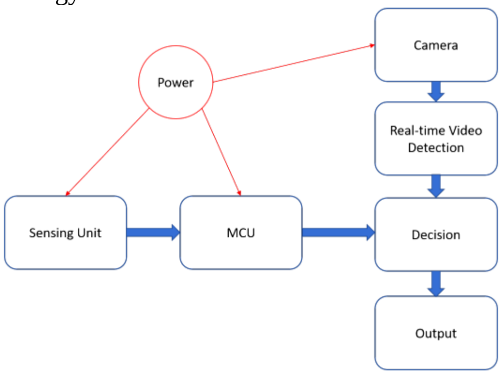

Fig 1: Architecture of the proposed design.

Whether an individual is using a mask or not in a photo can be determined via face mask detection. Actual position detecting finds the actual range across two persons in a photo after first identifying them in the image. Investigations have been carried out to identify face masks and sensory distance in the gathering ever since the COVID-19 outbreak started. Principal Component Analysis was used by [9] to conduct facial recognition on both masked and unmasked faces. The precision of the recognition, however, rapidly declines. Steffen et al. [10] also conducted a thorough investigation to determine the effects of mask use on the general public, some of whom may be infections in humans contagious in New York and Washington. Jin et al. [11] used an actual video footage database and a technique to show how to identify any video monitoring operations. Most of the methods cannot reliably identify behavior including individuals wearing masks in a real-time setting. However, there is no traditional technique for determining how much of a security danger those who wear masks provide.

To eradicate the earlier mentioned limitations of traditional safety systems and environmental monitoring, we are proposing a new hybrid approach consisting of the inclusive features combines and with unique remedies according to the aforementioned demerits of previous research: Automatic helmet detection using computer vision and deep learning. Automatic mask detection to prevent the spread of COVID-19 among industrial workers. We monitor and regulate the environment inside the industrial workplace using sensors to ensure the environmental cleanliness and reliability.

3. Description of the System

We propose to create a low-cost, IoT-based monitoring node to increase the representatives of environment condition and safety monitoring, as well as to be an alternative for small towns or industries that need to monitor their environment in a preventive manner. The nodes would have camera, dust, gas, temperature, humidity, noise and UV radiation sensors. In addition, a website is to be set up to view geographically based real-time data, generate reports and alerts on the basis of predefined parameters. We also propose to create a system that would monitor and control environmental safety by simply detecting wearable mask and helmet for each individual associated within an industry. Also, the insider environmental conditions such as dust particles, UV radiation, temperature and humidity, noise, lethal gas etc. are monitored and compared to the optimal parameters. The system provides an indication if the environmental condition is unsafe for human being.

The IoT device has four basic tasks which are – sensing environmental parameters, processing sensor data, establishing an exchange of processed data, supplying power to the whole process. Thus, the physical device has two active units that are: Comprises numerous sensors to detect UV index, Particulate matter, Noise, CO level, Temperature, and Humidity. The MCU Comprises the ESP32 Node MCU development board with required circuitry. The microcontroller unit functions as the system's "brain." Its responsibility is to collect unprocessed sensor data, comprehend of it as needed, and carry out the appropriate commands. The ESP32 Node MCU from Espressif Systems has been selected for the project as the appropriate design board/MCU following thorough examination.

As there is no existing dataset for industrial helmets, we had to make our own dataset to conduct the research work. We have created a dataset by taking the picture of ourselves wearing mask and helmet, without mask or without helmet. The dataset comprises of a total of 2000 images consisting of two class: Class A (with both mask and helmets) and Class B (the rest of circumstances). The new split the dataset in ration of 80:20 for training and test splits. We train the dataset into our novel CNN architecture. Then we have used our train model to conduct real-time video detection of helmet and masks using OpenCV framework.

4. Methodology of the Industrial Safety System

(CNNs) are similar to conventional ANNs in that they are made up of neurons that learn to optimize themselves. The fundamental building block of numerous ANNs, each neuron will continue to take in input and carry out an action (such as a scalar product followed by a non-linear function). The network infrastructure will still represent an unique perceptual coding scheme from the incoming raw picture vectors to the category score at the end (the weight). There are three different kinds of stages in CNNs. Convolutional, pooling, and fully-connected layers are what these are. A CNN structure is created once these layers are combined. The input layer will store the image's pixel values, as with other ANN variants.

The convolutional layer will calculate the specific formula among the parameters of the input volume-connected zone and the neurons whose output is related to particular regions of the intake. The goal of the rectified linear unit, also known as ReLU, is to activate the output of the earlier layer's stimulation by applying an "elementwise" kernel function, including gaussian. To substantially reduce the number of variables in that activation, the pooling layer will then essentially down sample along the encompasses a vast of the input. The fully-connected layers will next carry out the identical tasks as in conventional ANNs and make an effort to derive output values from the activations, which can then be applied to categorization. Additionally, it is proposed that ReLU be applied in between these layers to enhance the effectiveness.

The model consists of a total of six layers including input and output layer. The CNN layers have 64, 32, and 32 nodes respectively. The dense layer holds 1024 nodes. In between the convolutional layers max pooling layer is used and as activation function ReLU is applied. After the convolutional layer, a fully connected dense layer is added with a dropout of 0.3. As binary classification is required for the work, sigmoid activation function is used in the final layer. For loss calculation, binary cross-entropy or log loss is used and for the optimization Adam applied with a learning rate of 0.001. The architecture of the CNN is depicted in the Figure 2.

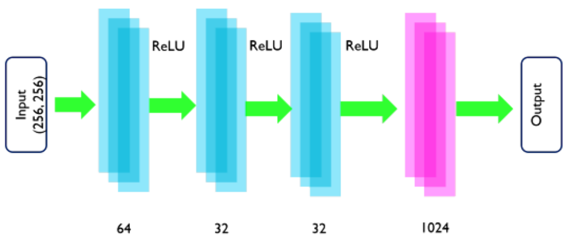

Fig 2: Architecture of CNN.

5. Experimental Setup of the Environmental Monitoring System

The main software required here is the widely used Arduino IDE. The IDE is used to program the NodeMCU in the C++ programming language. The reason for choosing this IDE over other IDE or MCU programming software is that it provides a free of cost, easy, and familiar environment for programming with a user-friendly interface, wide support of ESP32 boards, and modules, and easy debugging. All that is needed to do here is to add the NodeMCU and other sensors to the IDE using the built-in board manager which is a fairly easy task. A circuit layout was designed and implemented to convey the task. The data from the sensors were interfaced using the IDE.

The prototype was deployed on the rooftop which doesn't completely represent all the collective parameters except temperature, humidity, and UV index as other parameters like noise and PM 2.5 level tends to vary according to the area. The final device will be deployed over various locations of a designated area to measure more accurate collective readings.

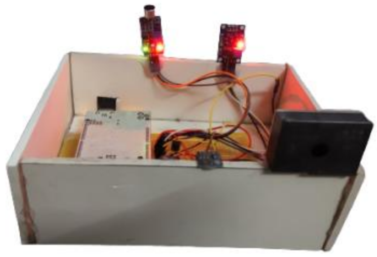

Fig 3: Prototype of the system implementation.

6. Performance Evaluation of the Industrial Safety System

Analyzing the fig. 6 test-train, it can be observed that the model fitted properly on the featured dataset. The blue line indicates training accuracy and the orange line indicates the validation accuracy for respective epochs. The validation accuracy achieved in the x^{th} epoch is y. In the fig.5, it can be said that the train and validation loss are very minimal at the value of x and y respectively. The blue line indicates training loss and the orange line indicates the validation loss for respective epochs. This fig 4. also represents that the model performed immaculately on the custom dataset.

From the Accuracy vs epoch curve, we can see the training accuracy and validation accuracy relation. The training accuracy is 98.02% and training loss is 8.48. The test accuracy is 95.14% and testing loss is 15.61.

From the Accuracy vs epoch curve, we can see the training accuracy and validation accuracy relation, and it is seen that there are no major over-fitting or under-fitting problem in the model.

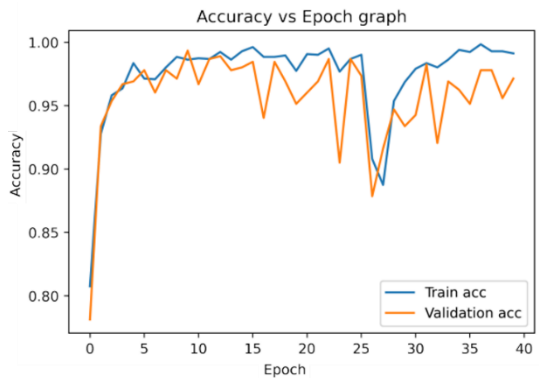

Fig 4: Accuracy vs epoch graph.

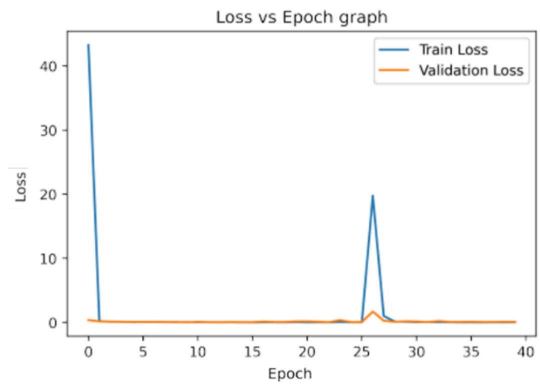

Fig 5: Loss vs epoch graph.

7. Real-Time Monitoring of the Inclusive System

Real-time monitoring involves gathering and archiving performance indicators for data as it travels across your network. In order to know how your networks, apps, and services are working, it includes monitoring and real - time processing from devices connected. Users can use the act of continually obtaining data to take immediate action when issues develop. However, this wasn't always necessary. A real-time dashboard is a sort of representation that has the most recent data accessible dynamically upgraded. These representations are helpful for spotting new patterns and tracking performance because they combine real feedback with historical data. Real-time dashboards frequently include time-sensitive data, including as performance information, quarterly results, and item statistics.

The real-time detection is done through the model implementation using the camera and implying the optimized model weights. The model is well trained and can detect masks and helmets in real-time scenarios and can feed the data to the server where sensor data also meets and a decision arises whether industrial safety is compromised or not. The system will not ring an alarm only if the safety conditions are met that is the mask and helmet should be worn by everyone and the environment quality should meet the ideal values.

Fig 6: Dashboard of the monitoring system.

Dashboard, shown in fig. 6, in our task is depicted. The dashboard shows the sensor values online and the real-time detection using computer vision. The image board identifies and detects whether both mask and helmet are worn by an individual and the numbers indicate the ideal values regarding each sensor. The fluctuations colored in green show one parameter has good enough conditions comparing the ideal and the red fluctuations indicate the parameter is less suitable comparing the ideal environmental parameters.

8. Conclusion

In order to enable total control over all industrial operations, Industry 4.0 integrates automation and information systems. Industry 4.0 aims for fully automated industries, yet there will still be a need for professional assistance and human supervision. For the protection of the employees and industry professionals, many of these industries have a variety of safety regulations that must be upheld. The requirement to always wear masks at work has been highlighted with the introduction of COVID-19 in 2019. Helmets and other essentials are also essential. We must also keep an eye on and control the atmosphere inside the industrial workplace because most industries are dangerous at some points. With these requirements in mind, we propose an intelligent industrial safety and health monitoring system that can detect workers wearing helmets or masks or not in real time. It can also monitor the environmental conditions within the industry and issue real-time warnings for any abnormal conditions. In our work, we have achieved high accuracy and precision in intelligent safety monitoring and environmental monitoring in industries.

References

[1] L. Huang, Q. Fu, M. He, D. Jiang, and Z. Hao, “Detection algorithm of safety helmet wearing based on deep learning,” Concurrency and Computation: Practice and Experience, vol. 33, no. 13, p. e6234, 2021.

[2] A. H. Rubaiyat, T. T. Toma, M. Kalantari-Khandani, S. A. Rahman, L. Chen, Y. Ye, and C. S. sconstruction safety,” in 2016 IEEE/WIC/ACM International Conference on Web Intelligence Workshops (WIW). IEEE, 2016, pp. 135–142.

[3] A. Afkhamiaghd and E. Elwakil, “Preliminary modeling of coronavirus (covid-19) spread in construction industry.” Journal of emergency management (Weston, Mass.), vol. 18, no. 7, pp. 9–17, 2020.

[4] T. Alhmiedat et al., “A survey on environmental monitoring systems using wireless sensor networks.” J. Networks, vol. 10, no. 11, pp. 606– 615, 2015.

[5] F. Chen and J. Ma, “An empirical identification method of gaussian blur parameter for image deblurring,” IEEE Transactions on signal processing, vol. 57, no. 7, pp. 2467–2478, 2009.

[6] S. Du, M. Shehata, and W. Badawy, “Hard hat detection in video sequences based on face features, motion and color information,” in 2011 3rd international conference on computer research and development, vol. 4. ieee, 2011, pp. 25–29.

[7] R. Lienhart and J. Maydt, “An extended set of haar-like features for rapid object detection,” in Proceedings. international conference on image processing, vol. 1. IEEE, 2002, pp. I–I.

[8] C.-Y. Wen, S.-H. Chiu, J.-J. Liaw, and C.-P. Lu, “The safety helmet detection for atm’s surveillance system via the modified hough transform,” in IEEE 37th Annual 2003 International Carnahan Conference on Security Technology, 2003. Proceedings. IEEE, 2003, pp. 364–369.

[9] M. S. Ejaz, M. R. Islam, M. Sifatullah, and A. Sarker, “Implementation of principal component analysis on masked and non-masked face recognition,” in 2019 1st international conference on advances in science, engineering and robotics technology (ICASERT). IEEE, 2019, pp. 1–5.

[10] S. E. Eikenberry, M. Mancuso, E. Iboi, T. Phan, K. Eikenberry, Y. Kuang, E. Kostelich, and A. B. Gumel, “To mask or not to mask: Modeling the potential for face mask use by the general public to curtail the covid-19 pandemic,” Infectious disease modelling, vol. 5, pp. 293–308, 2020.

[11] C.-B. Jin, S. Li, and H. Kim, “Real-time action detection in video surveillance using sub-action descriptor with multi-cnn,” arXiv preprint arXiv:1710.03383, 2017.