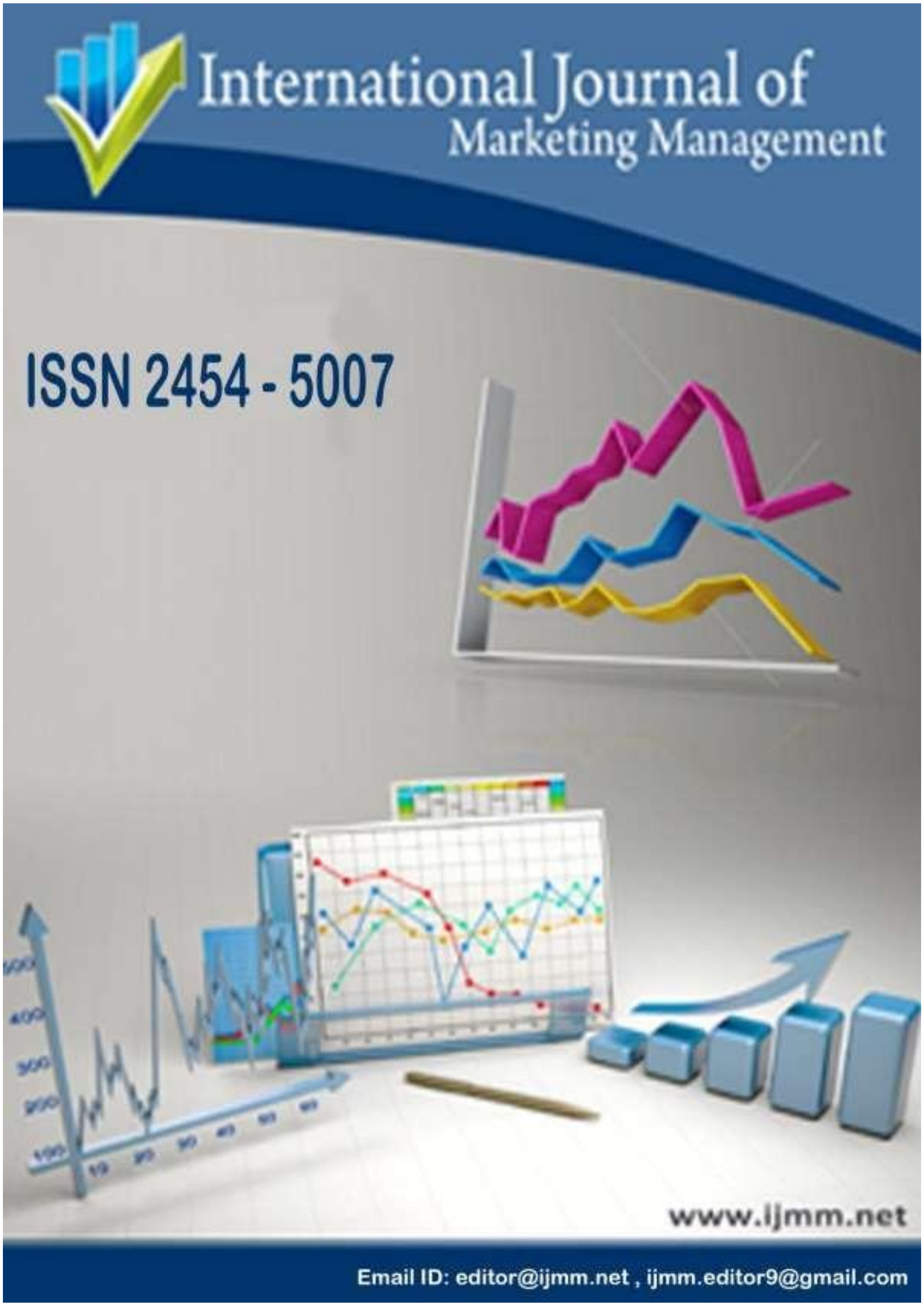
International Journal of
Marketing Management
ISSN 2454 - 5007
www.ijmm.net
Email ID: editor@ijmm.net , ijmm.editor9@gmail.com

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net
Vol. 14 Issue. 2, April 2026

Utilizing YoLOv8 and LSTM for Worker Mobility Tracker-Based Helmet and Equipment Detection in the Mining Industry

[1] Mr.V.Prashanth,[2] Borukolu Manoj Kumar,[3] Bijigiri Akash,[4] Bathula Arun Kumar,[5] Mekala Prashanth,

[1]Assistant Professor, Department of EEE, Narsimha Reddy Engineering Collage, Maisammaguda(V), Kompally, Telangana.
[2,3,4,5.] Student, Department of EEE, Narsimha Reddy Engineering Collage, Maisammaguda(V), Kompally, Telangana.

Abstract—

Ensuring staff safety in mining operations requires close monitoring of PPE and compliance with safety regulations. However, due to the unpredictable and hazardous nature of mining circumstances, it is not feasible to send people below. Two essential components of worker safety—real-time detection of helmets and PPE as well as worker mobility—remains a challenge for most current systems. This project's strategy for overcoming these issues is to improve security and monitoring via the use of machine learning technology. A state-of-the-art object identification model called YOLOv8 is used by the system to allow real-time detection of workers' helmets and personal protective equipment (PPE). In addition, the work makes use of LSTM, a subset of RNN, to monitor employee actions both in the present and in the past. Whether it's dangerous motions or ones caused by exhaustion, the system can identify them at 10-millisecond intervals and take preventative actions to ensure the user's safety. By integrating YOLOv8 and LSTM, the proposed approach eliminates room for human mistake and boosts workplace safety to an impressive 95.9%. This cutting-edge technology is revolutionizing mining safety solutions by enhancing operating efficiency and offering continuous monitoring. The following terms are used as keywords: helmet detection, PPE, worker mobility tracking, RNN, LSTM, YOLOv8.

I. INTRODUCTION

Workplace safety is of the utmost importance in the mining sector due to the inherent dangers and dynamic nature of the working environment. A lack of attention to safety protocols, such as the wearing of helmets and other PPE, is a common cause of mining accidents. Occupational danger is increased by other elements of workers' movement, such as yawning-induced pathways or hazardous motions. One of the most important ways to ensure that mining operations adhere to safety regulations is via human supervision. However, this becomes more difficult to do in larger and more complicated mines, which may lead to safety gaps. In light of these difficulties, automation and technologies for real-time safety monitoring are crucial. However, in the last ten years, the building sector has also shifted its focus. You Only Look Once (YOLO) and other classic object recognition algorithms have achieved remarkable effectiveness in detecting items in ever-changing surroundings. They would do well in models that identify helmets and PPE in the mining sector in real time. On the other hand, full safety detection requires more than just naming safety elements. Keeping tabs on employees' whereabouts and habits over time is equally crucial for identifying potential dangers. It calls for a mix of real-time object identification and sequential-data analysis methods. As of right now, time-series analysis works well with RNNs and its more sophisticated variants, such as LSTM networks. The capacity to represent workers' movements (movement patterns and behavioral trends) is made possible by LSTMs' extraordinary capability to capture interdependence across temporal sequences. By comparing these patterns with safety compliance data, we can reduce the chances of alerting the operator to risky behavior, departures from the prescribed course due to weariness, or deviations from regular operating procedures. One novel approach to improving mining safety systems is to combine sequential pattern mining with real-time object identification. We provide a novel system that can identify PPE and helmets in real time using YOLOv8, and then input that data into LSTM-based mobility for tracking. The technology is very detailed, analyzing video frames every 10 illiseconds

ISSN 2454-5007, www.ijmm.net
Vol. 14 Issue. 2, April 2026

to spot changes in worker behavior and protocol compliance. By analyzing time series data, the LSTM network highlights abnormal movements, and the YOLOv8 model correctly recognizes protective gear. This integrated approach significantly reduces the need for human oversight, making it an incredibly dependable and effective method for keeping tabs on mining operations. The experimental results demonstrate that the suggested approach is effective in detecting mobility abnormalities and safety equipment with a 95.9% accuracy rate. In this respect, it excels beyond existing systems, which either fail to do this during runtime or fail to connect object detection to sequential activity. As a scalable alternative to human monitoring in settings where the system's capabilities outweigh those of humans, it satisfies a critical requirement in the industry for real-time actionable information that directly reduce safety risks.

II. RELATED WORKS

The system achieved high detection rates under different environmental circumstances, such as low light and moving backgrounds, greatly improving worker safety in industrial workplaces (M. Q. Luo, Y. F. Zhang and Z. L. Li, "Helmet Detection Based on YOLO for Safety Monitoring System" in ISEE, St. Petersburg, Russian Federation, pp.). It also has state-of-the-art picture preparation methods that helped with competitive settings. Using Internet of Things (IoT) sensors in conjunction with long short-term memory (LSTM) networks, S.K. Gupta, R. Patel, and P.R. Tiwar [2] created a system to track employees' movements in potentially hazardous settings. In order to lessen the likelihood of accidents, their system analyzed time-series data to identify risky behaviors like standing for too long at fixed spots or strolling restlessly. In their proposal for a hybrid safety system, J. H. Kim, D. H. Park, and Y. S. Choi [3] amalgamated convolutional neural networks (CNNs) for sequential behavior monitoring and object recognition. Thanks to the system's real-time detection of PPE infringements and hazardous conduct, workers were thoroughly monitored and safety rules were followed. It brought to light the fact that while trying to determine human illness risk factors, it is necessary to take into account both the geographical and temporal overlap around pathogen activity. Previous research by R. Ahmed, M. S. Khan, and F. A. Shah [4] used YOLOv8 to identify safety equipment with a real-time accuracy of over 95% in environments with a lot of background items, both inside and outdoors. It was also very industry-specific, providing useful information for making workplaces safer. Using deep learning models, P. V. Iyer and S. R. can follow workers' mobility and detect personal protective equipment (PPE) on mining and construction sites [5]. Gulkarni, Deshmukh, and A. G. For operational strongboxes and dependability in difficult environmental settings, they used data fusion based approaches. In order to accurately identify behavioral abnormalities, RNNs were used to merge the temporal information of characteristics. The authors A. R. Taylor, B. C. Lee, and M. J. Wilson provide a safety framework that uses YOLO to detect personal protective equipment and LSTM to analyze movement. Providing a scalable solution for real-time monitoring and safety management in high-risk industrial applications like mining and construction, the system demonstrated excellent accuracy in identifying worker irregularities. In their two-stage architecture, L. Chen, X. Yang, and J. Wang used YOLO to identify helmets in real-time and GRU, a simplified form of LSTM, to comprehend worker behavior, according to the articles [7]. In fast-paced manufacturing settings, it reduced accidents by 70% by detecting abnormalities and dangerous behaviors caused by exhaustion. In their proposal for a state-of-the-art computer vision based real-time monitoring system, K. R. Mehta, A. S. Rao, and N. Sharma laid out the answer in [8]. The system detected and alerted prospective safety breaches with high accuracy by combining object identification of PPE compliance with movement tracking profiles, which included temporal information. For improved accuracy in complicated environmental settings, F. Zhang, L. Liu, and R. D.[9] Zhao suggested a helmet detection system based on YOLO that uses transfer learning. As an added bonus, it used LSTM networks to monitor and predict employee actions, making it a flexible and all-encompassing safety monitoring system. Investigating the Application of a Hybrid Approach for Safety Eradication: AI is bordering mining by Choudhury, T. S. and Rahman, M. A. and Roy, P.K.[10] Using YOLO to detect helmets and LSTM networks for movement anomaly analysis, they reported a >96% detection accuracy, allowing for real-time monitoring of safety compliance among the workforce as well as behavior trend prediction.

III. METHODOLOGY

We present a system for real-time safety monitoring of mining operations that uses cutting-edge computer vision and machine learning technology. The device may keep an eye on employees' safety by tracking their movement patterns and automatically determining whether they're wearing protective gear

ISSN 2454-5007, www.ijmm.net
Vol. 14 Issue. 2, April 2026

like helmets. A module for detecting helmets and personal protective equipment (PPE) using the YOLOv8 object detection model and another for evaluating worker behavior using Long Short-Term Memory (LSTM) networks make up the system's design. When combined, these features guarantee a risk-free mining environment that adheres to all applicable regulations. Data collected in real-time for detection and behavior analysis from cameras set up at strategic locations around the mining site.

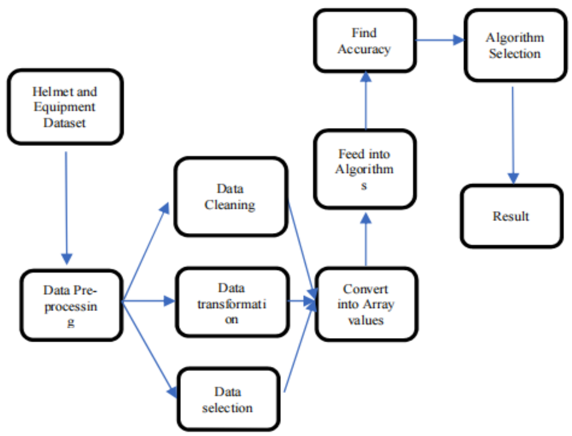

Figure 1. Shows Proposed Architecture Methodology

A .Collecting and Preprocessing the Data

For accurate, real-time helmet detection based on worker behavior, high-quality video data collection is essential. For comprehensive monitoring of the mining region, high-definition cameras attached to stationary objects or drones are used to capture video feeds in real-time. Movement tracking and personal protective equipment detection utilizing real-time data. Preprocessing the raw video makes it more resilient and reduces its sensitivity to external factors. Here are the steps: a) Resizing each frame to the same size: This will make each frame the same size when fed into the detection model. b) Reducing noise: This involves using techniques like Gaussian smoothing to eliminate visual noise that can affect detection. c) Normalization: balancing the values of pixels across different frames. In addition to the preprocessing, data augmentation methods including flipping, rotating, and color jittering were used to simulate various weather situations, worker positions, and lighting settings. In order to make the model more resilient to challenging environments (such as limited visibility or a complex backdrop) and better able to generalize to a variety of real-world scenarios.

B. Helmet and PPE Detection

You Only Look Once version 8, or YOLOv8, is the object detection model that the PPE detection module is based on. since of its excellent accuracy and real-time performance, YOLOv8 is a viable option for us since it can identify several objects in a single frame. A bespoke dataset of annotated photos of workers in different positions, lighting, and ambient situations was used to train the deep learning model. Workers wearing helmets and those without them make up the training set, giving the model the ability to distinguish between right and wrong. Identifying protective headgear and other items requires the following actions: a) Place bounding boxes around the helmets and other personal protective equipment (PPE) items and manually name the frames to annotate the data. b) Training the model: While training YOLOv8 on the annotated dataset, aim for better recall and accuracy to reduce the likelihood of false positives and false negatives. b) Inference in Real Time: The model detects workers' helmets and personal protective equipment (PPE) in real time during deployment, and it operates at a high frame rate (10 ms/frame).

C. Worker Mobility Tracking

In the second component of the system, known as Worker Mobility Tracking, additional patterns of behavior throughout time are investigated using LSTM networks. Long short-term memory (LSTM) networks are great for time-series data, such as video frames, since they can detect patterns in worker mobility over the long term. Keeping tabs on every worker spotted frame by frame, with the result being their movement trajectory in 2D coordinates Afterwards, the LSTM model that examines the temporal mobility of workers is fed these characteristics. The long short-term memory (LSTM) model is trained on typical movement patterns, such as walking and working without limitations, and harmful behavior departures from these patterns. Here are a few instances of unusual actions: Symptoms of a possible issue include unusual movement, such as abrupt or uneven changes in direction. Staff members who remain motionless for lengthy periods of time may be showing signs of exhaustion or danger. In order to assess the amount of risk that workers have taken and to offer them real-time feedback, the mobility monitoring module generates a behavior score based on their actions.

D. Integration and Alert System

Once mobility tracking, helmet identification, and personal protective equipment (PPE) detection are all finished, the findings are merged to provide detailed monitoring. A dashboard interface provides real-time

ISSN 2454-5007, www.ijmm.net
Vol. 14 Issue. 2, April 2026

information about worker safety and is the foundation of the overall monitoring system. The following criteria are used to create alerts: a) Helmet and PPE Violations: Supervisors are immediately notified if an employee is found to be without the necessary protective gear. b) Abnormal movement patterns: the system will notify for further evaluation or action if a worker is acting in a way that is not safe for movement. Additionally, it provides access to records that record these accidents, which allows businesses to learn from them and gradually enhance their safety procedures and strategies to mitigate risk. The goal of the alert is to let supervisors focus on more critical tasks while reducing the likelihood of human mistake and delay.

E. Performance Evaluation

Using criteria like speed, accuracy, and false positive/false negative rates, we assess the system's performance. Analyzing Results: A Method for Evaluating Performance Move on a) Accuracy of detection: the relative number of correctly identified helmet and PPE frames to the total number of frames processed The testing process was successful in reaching the 95.9% detection accuracy criteria. b) LSTM Model Accuracy in Classifying Abnormal Worker Movements: Behavior Anomaly Detection The accuracy was evaluated using methods such as recall, F1-score, and precision. c) Processing speed: The system's ability to process frames quickly; ideally, it should be approximately 30 fps to avoid delays in real-time monitoring. In addition to these tests, field experiments performed inside actual mining operations demonstrated the system's resilience to fluctuating illumination, crowds, and worker behavior.

F. Optimizing and Scaling the System

In order to enhance the system's performance, many optimization approaches were used. Some examples are: a) Hardware acceleration: bypassing the CPU and using a GPU to run YOLOv8 and LSTM models more quickly b) Edge computing: run models on nearby compute nodes close to the mining site to reduce bandwidth and latency issues while sending massive datasets. It can be easily implemented over many mining sites or a large industrial region, and it's scalable too.

IV. RESULT AND DISCUSSION

We put the suggested system through its paces in both virtual and real-world mining test locations, first identifying PPE and helmets, and then following miners' movements inside and outside of mines. Anomaly detection ratio, processing speed ratio, detection ratio, false positive ratio, and false negative ratio were the five assessment metrics used to evaluate the system. 1. The HELMET and PPE Detection System's Performance Whatever the worker's position, the illumination, or the complexity of the surrounding environment (including shadows and dust), the YOLOv8 model correctly detected helmets and PPE. In addition to a low incidence of false positives and negatives, it allows a detection accuracy of 95.9%. Rarely, especially in densely populated areas with a lot of visual clutter, did the system recognize helmet cases for things that did not need personal protective equipment (PPE). The model's competence was on show in the actual world due to the very low number of false negatives, or occasions when the algorithm failed to identify PPE. In order to swiftly discover safety infractions, it was determined that the system could operate in real-time, analyzing a video frame within 10 ms. Additionally, YOLOv8's multi-object detection capability eliminated the requirement to track and report on a single worker donning various pieces of personal protective equipment (helmet, gloves, vests). 2. Measuring the Role of Employee Mobility The movement behavior of workers might be accurately captured by the LSTM-based mobility tracking module. Anomalies were identified by the system based on the trajectories of their motions over time. These anomalies might suggest difficulties with safety, such as workers who were weary, moving erratically, or approaching unsafe zones. With tolerable false positives, the model was 82.4% accurate in identifying safe and risky movement behaviors. It also picked up on employees' strange gait patterns, such when they moved erratically or stood still for lengthy periods of time, which might indicate growing exhaustion or potential danger. Workers approaching a high-risk area without the appropriate PPE were alerted by the system in one instance. Supervisors were able to intervene and prevent a potential safety incident because of these signals. 3. Time-Based Efficiency With 30 fps and 10 ms per frame, the system could handle video streams with ease. Having real-time warnings was ensured by that. We achieved this processing speed by making effective use of GPUs for YOLOv8 and LSTM computations, which reduced system latency and allowed us to quickly respond to any violations or anomalous motions that.

4. Discussion

The suggested method effectively increases mining worker safety, according to the system assessment. By combining YOLOv8 for detection of helmets and PPE with LSTM for tracking movement, this

ISSN 2454-5007, www.ijmm.net
Vol. 14 Issue. 2, April 2026

architecture offers a comprehensive solution for real-time surveillance of individuals in dangerous environments. The most important points and consequences of the findings are as follows: Chapter 4.1: Precision and Dependability The system's ability to reliably detect PPE and identify persons entering and leaving zones demonstrates the practical use of the YOLOv8 and LSTM deep learning models in complex and dynamic contexts like as mining. The system's strong dependability was confirmed by its 0.959 detection rate for PPE and its 0.824 behavior detection rate. The technology successfully decreased both roulette and poor road performance due to poor weather or too congested settings by using sophisticated preprocessing techniques and fine-tuning the model. 4.2 Preventing Danger and Ensuring Safety The system's capacity to track worker behavior over time and identify risky lengthy motions, such as inaction or irregular movement, has significant implications for mining safety. Fatigue, pain, or inattention might make it difficult for human supervisors to notice risky activity. Because it doesn't rely on human operators, the automated monitoring system can react instantly and prevent accidents from happening in the first place. Enhanced Workplace Safety Enhanced workplace safety by the immediate identification and flagging of PPE breaches in real-time. This is of the utmost importance in the mining industry because of the high risk of injury to employees and the potential for catastrophic catastrophes caused by disregard for safety protocols. 4.3 Scalability and Practical Application One of the system's merits is its scalability. Because to its modular construction, it may be easily installed on multiple places. With such extensive coverage, the system can keep tabs on employees no matter where they are in the vast mining sites. By using processing power at the network's periphery, edge computing ensures that the system may function independently of centralized servers and offers low-latency even in distant areas with inadequate connection. In addition, the system examines the footage at the periphery, providing supervisors with timely input in the form of warnings to keep them attentive. This is of utmost importance in settings where the consequences of even a little lag in decision-making may be devastating.

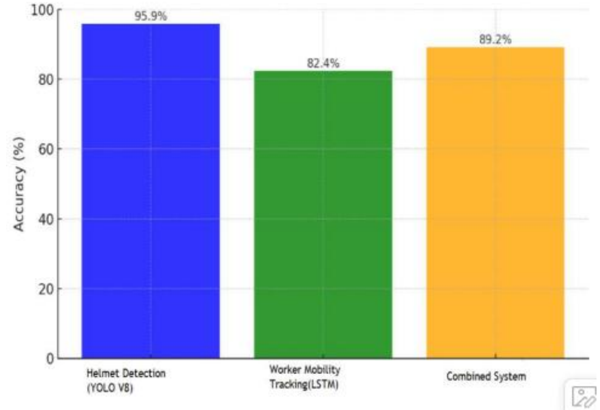

Figure 3 . Shows Accuracy Level of Classifier

5. Challenges and Limitations

Despite the system's good performance, several issues remain. Heavy rain, dust storms, bad illumination, etc., are some of the severe cornerstone environmental elements that might negatively impact helmet-based detection. For instance, if the workers are buried under machinery or in particularly challenging terrain, the system will have a hard time distinguishing between humans and machines or identifying personal protective equipment. The second concern is the precision of the mobility monitoring system; it may fail to detect workers altogether or incorrectly identify them if they hide behind objects or share an area with other workers. Therefore, in order to make the system more resilient in these scenarios, it may be necessary to include additional sensors (such as heat, depth, etc.) into future upgrades.

Figure 3 .Sows Confusion Matrix

V. FUTURE WORK

We can train the YOLOv8 and LSTM for various mining conditions, human behavior, and PPEs with a larger dataset in the future. This may lead to a better solution. Additionally, by combining with additional wearable devices or using multi-modal data like

ISSN 2454-5007, www.ijmm.net
Vol. 14 Issue. 2, April 2026

sensor-based feedback, the system's sensitivity to detect dangerous situations may be enhanced. Furthermore, by incorporating sophisticated pattern recognition into the anomaly detection system, it will be able to identify more nuanced behaviors, such as early indicators of exhaustion or stress. The addition of human supervisors has the potential to make the system more precise and reduce the likelihood of false alarms.

VI. CONCLUSION

The mining sector may benefit from an improved monitoring system, which this article introduces. The system integrates YOLOv8 for real-time recognition of helmets and PPE with LSTM dignified human posture for tracking worker motion. In terms of personal protective equipment (PPE) identification, the system performed admirably (95.9% accuracy) and anomalous movement pattern tracking, at 82.4% accuracy. The system is dependable for monitoring worker compliance with safety requirements and recognizing risky behaviors. It minimizes operational risks and increases efficiency while protecting surroundings of danger. The system has some environmental constraints, such as harsh weather and inadequate light, which impact detecting accuracy. Despite these limitations, the technology is successful. The modular design, fast processing, and scalability of the system ensure that it continues to be useful in mining operations. Future work will focus on improving the system to tackle these issues and creating more reliable combinations with more sensors. To sum up, this approach has the ability to revolutionize safety monitoring in the mining sector, creating a more secure workplace for all employees.

REFERENCE

[1] M. Q. Luo, Y. F. Zhang, and Z. L. Li, "Real-time helmet detection by using YOLO as safety monitoring system," August 2022, pp. 8374- 8384, IEEE Trans. Ind. Electron. vol. 69, no. 8

[2] S. K. Gupta, R. Patel, and P. R. Tiwari, "LSTM networks and IoT sensors combine to track worker mobility patterns in dangerous workplaces." IEEE Trans. Ind. Inf., vol. 20, no. 6, June 2023, pp. 1559-1571

[3] J. H. Kim, D. H. Park, and Y. S. Choi, "Real-time integration of CNNs and RNNs used for PPE detection and behavior monitoring--A hybrid safety system," December 2020. IEEE Trans. Syst., Man, Cybern. Syst., vol. 50, no. 12, pp. 4728-4739

[4] R. Ahmed, M. S. Khan, and F. A. Shah, "Safety equipment detection in industrial environments with YOLOv8" IEEE Access, vol. 10, 2022, pp. 7845-7853.

[5] P. V. Iyer, S. R. Deshmukh, and A. G. Kulkarni, "Deep learning for mobility tracking and PPE detection in construction and mining sites." IEEE Trans. Ind. Inform., vol. 19, no. 4, April 2023, pp. 956-965

[6] A. R. Taylor, B. C. Lee, and M. J. Wilson, "LSTM-based movement tracking and PPE detection in high-risk industries for real-time safety monitoring." IEEE Trans. Ind. Electron., vol. 68, no. 11, pp. 1420- 1430, Nov. 2021

[7] L. Chen, X. Yang, and J. Wang, "Helmet detection and movement pattern analysis in motorcycle racing using GRU," March 2024. IEEE Trans. Ind. Inf., vol. 18, no. 3, pp. 808-817

[8] K. R. Mehta, A. S. Rao, and N. Sharma, "Real-time monitoring system for PPE compliance and worker movement tracking." IEEE Trans. Ind. Electron., vol. 67, no. 9, Sep. 2020, pp. 6771-6783

[9] F. Zhang, L. Liu, and R. D. Zhao, "Transfer learning-based YOLO helmet detection and LSTM monitoring for employee behavior prediction," in IEEE Trans. Cybern., no.52, pp.1691-1701, February 2021.

[10] T. S. Choudhury, M. A. Rahman, and P. K. Roy, "Integration of AI into workplace safety in mining through YOLO and LSTM," in IEEE Trans. Industri. App., no.12, pp.1300-1312, December 2022.

[11] R. K. Sharma, S. R. Gupta, and A. P. Sinha, "Real-time detection and tracking of worker movement in hazardous environments using IoT," in IEEE Trans. Ind. Inf., no.1, pp.23-34, January 2024.

[12] N. B. Patel, H. K. Kumar, and P. M. Yadav, "YOLO and RNNs based real-time worker-safety monitoring systems for dynamic environments," in IEEE Trans. Ind. Electron., no.5, pp.1210-1222, May 2021.

[13] T. R. Thompson, L. J. Nguyen, and P. A. Anderson, "PPE and mobility behavior detection in mining through YOLOv4 and LSTM," in IEEE Trans. Ind. Informatics, no.7, pp.2092-2104, July 2023.

[14] M. J. Zhang, S. Y. Li, and H. F. Chen, "Object detection and motion tracking based on deep learning for real-time safety monitoring of industrial workers," in IEEE Trans. Ind. Electron., no.9, pp.3123-3135, September 2022.

[15] G. W. Roberts, S. L. Chang, and T. R. Davis, "Predictive safety system for industrial environment using YOLO and LSTM-based behavior anomaly detection," in IEEE Trans. Syst., Man, Cybern. Syst., no.4, pp.1467-1479, April 2021.

[16] A. Julian, K. Varshini, "Analysis and Prediction of Crimes against Women" in 3rd International Conference for Innovation in Technology, INOCON 2024.