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Machine Learning for Risk Assessment in Employee Safety Compliance

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ARTICLE INFO	ABSTRACT
Received: 12 June 2025 Revised: 22 Jul 2025 Accepted: 02 Aug 2025	Machine learning (ML) is revolutionizing employee safety compliance across multiple industries most notably, construction, manufacturing, and healthcare. In this paper, present the use of ML models decision trees, neural networks, and computer vision techniques - for predicting, monitoring, and mitigating workplace hazards. ML provides risk assessment by analyzing archival data, environmental conditions, and real-time inputs from IoT sensors and wearable devices for a continuous safety monitoring. In particular, XAI helps fill transparency and interpretability gaps, providing actionable insights. This study demonstrates the fundamental role that ML plays in decreasing the occurrence of accidents in the workplace and improving workplace safety and compliance while pushing for proactive risk management. **Keywords:** XAI, Machine learning, occurrence, compliance

Introduction

Acquisitions in high risk industries like construction, manufacturing, and healthcare are very important because employee safety compliance is a huge problem and accidents and injuries can have pressing consequences. Safety monitoring and risk assessment according to conventional methods, i.e., manual inspections and reactive strategies, have inherent limitations at controlling the accidents and guaranteeing compliance. Nevertheless, the arrival at machine learning (ML) appears to provide a radically innovative way of enhancing safety management. With large datasets from disparate sources such as historical incident records, wearable sensors and real time monitoring systems in hand, ML can predict the likelihood of risks, capture unsafe behaviours and generate actionable insights to initiate preventive actions. In this paper, explore how machine learning is transforming the way employee safety risk is assessed, highlighting usage cases, challenges and future possibilities to assist in improving workplace compliance with safety. (Zhong, X., She, J., & Wu, X. 2024)

Literature review

Machine Learning for Risk Assessment in Employee Safety Compliance

According to Varshney, K.R. and Alemzadeh, H., 2017. Risk assessment and safety compliance is being increasingly applied to using machine learning (ML) across different industries. In particular, the potential for ML to improve safety practises in high risk environments, including construction, manufacturing, and even healthcare, is truly incredible. However, recently research has demonstrated how ML models can be used to forecast, monitor and suppress workplace hazards to increase safety compliance and decrease accidents. Risk prediction is an important application of ML in safety compliance. However, a number of studies have shown that ML algorithms, especially supervised learning models such as decision trees, support vector machines, and neural networks can successfully predict accidents that might occur at workplace based on previous (historical) data. These risk factors models are based on factors like past incidents, environmental conditions use of equipment, and behaviour of the worker. As a result, for instance, developed a model that forecasts risk of safety violations in construction sites based on task characteristics and worker demographics. Along with risk prediction, ML can be applied to continuing monitoring of safety compliance. ML systems can take data

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from IoT sensor, wearable devices, video surveillance, and analyse them for unsafe situations conditions or behaviours in real time. Integrated into safety systems, these technologies alert supervisors to non-compliance with the intent to intervene rapidly. Additionally, unsupervised learning methods such as clustering or anomaly detection can reveal constrains in safety violations or discover anomalous risk factors. Ethical and interpretability concerns are presented at the intersection of machine learning and employee safety compliance. In safety sensitive contexts, where the ML models will be used, for the models to be effective, they need to be transparent and understandable to human decision-makers. Predictions are being made actionable and comprehensible through techniques like explainable AI (XAI), for instances that allow safety managers to understand their significance. Machine learning promises to aid in improving employee safety compliance by improving risk assessment, monitoring, and decision making. However, robustness, fairness and interpretability of these models has to be guaranteed.

Categories	No.	Value	Total number of NHU workers	Number of images
Weather	1	Sunny	2582	1000
	2	Cloudy	2249	1000
	3	Rainy	1684	1000
	4	Haze	2350	1000
Illumination	1	8:00-10:00 am	2120	1000
	2	10:00-12:00 am	2437	1000
	3	2:00-4:00 pm	2646	1000
	4	4:00-6:00 pm	2035	1000
Individual posture	1	Standing	1660	1000

Figure 1: SAFETY IN MACHINE LEARNING

(Source: Varshney, K.R. and Alemzadeh, H., 2017)

Machine Learning for Automatic Safety Compliance Detection in High-Risk Environments

According to Fang, Q et al., 2018. In high risk industries such as construction, machine learning (ML) has proven quite successful at increasing employee safety compliance. Being sure that safety protocols are being followed is one of the key challenges in these sectors — protective equipment, such as hardhats, are just one form that safety protocols can take. (Attar, Gharade, Khan, & Shekasan, 2022) Due to the time and error-prone nature of traditional manual inspection, more and more researchers have been interested in automatic safety compliance detection with help of ML. There has recently been a flurry of studies investigating the use of computer vision techniques for detecting non-compliance behaviours like non-compliance to wear hardhats. For instance, deep learning models like the Faster R-CNN has exhibited effectiveness in the use looked from surveillance videos, for example.

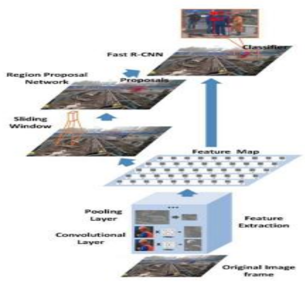

Figure 2: Framework of the proposed method

(Source: Fang, Q et al., 2018)

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In research, Faster R-CNN, a high precision/low latency object detection model, was shown to to be able to correctly identify workers without hardhats in a variety of construction environments. (Doval & Negulescu, 2024) Far field video data is analysed with these models, enabling scalable far field monitoring of large construction sites without close up cameras or human intervention. While applying machine learning to the general risk assessment in safety compliance goes beyond hardhat detection, it has already taken place. (Krishnamoorthy et al., 2024)

Category	Actual NHU	Predicted NHU
TP	YES	YES
FP	NO	YES
FN	YES	NO

Figure 3: Definitions TP, FP and FN for NHU detection

(Source: Fang, Q et al., 2018)

Having constructed ML models to predict accidents based on historical data, environmental factors, and worker behaviour, ML models have been used in construction and manufacturing. For example, decision trees and neural networks have been used as risk factors causing safety violations. IoT devices, wearable sensors, or sensors integrated into physical equipment (Vukicevic, A. M., et. al. 2024) provide real time data that can be applied to ML for live detection of unsafe practises (such as unsafe lifting, or hazardous movements) (Varshney and Alemzadeh, 2017). While ML based safety monitoring systems hold great promises, their interpretability and transparency is a critical requirement. Particularly, methods such as explainable AI (XAI) can support ensure that ML predictions are actionable and understandable by safety manager.As conclude, machine learning is a promising tool for enhancing safety compliance and assessing risk in employee safety, providing real-time, automated and scalable solutions for monitoring and preventing accidents in hazardous work environments. (Chen et al., 2024)

Categories	No.	Value	TP	FP	FN	Precision (%)	Recall (%)	Miss Rate (%)	Speed (s)
Visual range	1	Large	3374	226	280	93.7	92.3	7.7	0.212
	2	Middle	2065	91	102	95.8	95.3	4.7	0.207
	3	Small	1089	18	47	98.4	95.9	4.1	0.204

Figure 4: Precision, recall and miss rate ratios under different visual range

(Source: Fang, Q et al., 2018)

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Methods

Data collection and data processing

The first step in machine learning to improve the employee safety compliance is to collect data that helps giving an idea about history of incidents, safety violations, employee's demographics, job role, and environmental factors (Roughton and Crutchfield, 2015). Typically the data sources are safety reports, wearable sensor data, and real time monitoring systems. Preprocessing involves cleaning the data (dealing with missing values, fixing what is broken), normalising, and encoding categorical variables (i.e., one hot encoding). The feature engineering helps to get key factors like hazard types and employee experience. Class imbalances are addressing with techniques (oversampling/undersampling). High quality input for accurate risk predictions requires good data processing.

Methodology	Independent of reading range/ figure size	Independent of facial features	Independent of worker posture	Independent of partial occlusion	Independent of workers' coordination and participation
RFID [[19,24]]	×	√	√	√	×
Bluetooth+ pressure sensor[25]	×	√	√	√	×
Haar-like features [31]	×	×	√	√	√
Edge detection algorithms [32]	×	×	√	√	√
HOG+CHT [33]	√	×	×	×	√
HOG+SVM [8,34]	√	√	×	×	√
Faster R-CNN	√	√	√	√	√

Figure 5: Comparison of the applicability of various methods

(Source: Fang, Q et al., 2018)

Designing of Machine Learning Models

When it comes to designing machine learning models to adhere to security standards, choose algorithms such as decision trees, random forests, and support vector machines (SVM) to predict risk on the basis of past data. When feature selection techniques are used, such as recursive feature elimination (RFE) or principal component analysis (PCA), some variables are selected on which to improve model accuracy (Fang et al., 2018). For larger datasets, the deep learning models, (e.g., neural networks) can be used. The effectiveness of model is evaluated by these metrics such as accuracy, precision, recall & F1_score. That is, cross validation ensures model generalises well to new data. They aim to build models that characterise safety risk and features useful for improving compliance. (García-Madurga, Gil-Lacruz, Saz-Gil, & Gil-Lacruz, 2024)

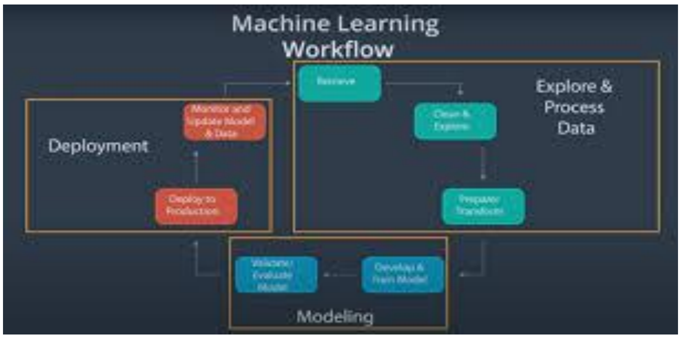

Figure 6: Design A Machine Learning System

(Source: https://medium.com/)

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Implementation and Deployment

Considering that machine learning models must be implemented into an already existing safety management system that monitors employee compliance in real time, it is imperative to consider real world implementations of such systems. Continuous data flow comes from sensors, IoT devices, and employee activities, and they are often processed in scalable infrastructure, such as a cloud, and may be visualised. The model ensures real time decisions, flags potential risks, and offers corrective recommendations, in addition to determining safety compliance (Podgorski et al., 2016). The model is retrained, and provided with regular updates, to keep updating the model and the accuracy of the model. The monitoring part includes dashboards for checking out the risk trend and performance. The model is refined based on feedback loops from safety officers. Maintenance of an effective risk mitigation, however, requires continuous monitoring, periodic updates and focus on adapting to changing safety conditions. (Doval & Negulescu, 2024)

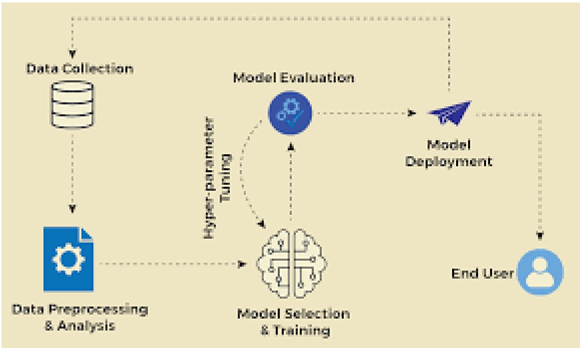

Figure 7: Implementation and Deployment

(Source: https://www.timeplus.com/)

Result

Predictive Analytics in Sales and Demand

The accuracy of forecasting in sales and demand forecasting has been greatly enhanced due to predictive analytics. Machine learning models such as time series analysis and regression can be used by predicting future sales when historical sales data, seasonality and market trends are used. With these models businesses can predict demand fluctuations and hence, optimise its marketing, production and inventory strategies (Rivas et al., 2011). This means that companies reduce stock out, minimise excess inventory and increase customer satisfaction. Predictive analytics also helps identify trends that would otherwise go unnoticed, in turn allowing smarter pricing, better supply and demand alignment and cost reduction. Taken together, these insights result in improved profitability and data driven decisions at the sales and supply chain level.

Innovation Strategies for Inventory Management and Replenishment

There has been innovation in inventory management, utilising machine learning, IoT sensors and real time analytics to drive major efficiency gains and cut costs. Inventory needs are the predicted by machine learning models in which the sales data, lead time, supply chain constraints are analysed to determine the stock levels and eventually reduce stockout or overstock situations (Zhang et al, 2015). Restocking accuracy and speed can be improved with the help of automating tools including AI based autonomous replenishment systems. Warehouses are increasingly using drones and robots to make itself better and run less error prone. Improved service levels, higher customer satisfaction, reduced

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excess inventory and cost effective inventory management are achieved with reduced service inventory leading to higher profitability and operational performance. (Park, J., & Kang, D. 2024)

Redesigning the Lines of Logistics and Supply

Improvements in operational efficiency and the reduction in delivery times and the increased flexibility to service customer requirements are the results of redesigning the logistics and supply chain lines. Typically in this redesign process you can adopt digital technologies such as blockchain for secure tracking, AI for routing optimization, and robotics to automate warehousing tasks. However, when combined, these technologies help these supply chains become smarter, swifter and more agile (Reese, 2018). The ability to reduce transportation cost, optimise routes, is one of the primary results of logistics lines redesign. AI algorithms can look for patterns on how traffic moves, patterns in the weather or the capacity of vehicles to recommend the best delivery routes. As a result, fuel consumption is lowered, delays are reduced and overall supply chain reliability improved. Real time tracking systems and the integration of IoT sensors throughout the supply chain give companies the ability to keep tabs on the flow of goods and inventory at all times (Komandla, 2017). It becomes more proactive to the point of identifying potential disruptions or delays before they become bigger problems. On the one hand, it can result in reducing inventory levels, which reduces carrying costs and reduces inventory carrying costs; on the other hand, advancing technologies helps companies streamline supply chain processes, improve delivery times and higher customer satisfaction. Revised logistics chains create a platform for greater responsiveness, higher scalability and better resource allocation, all of which create an edge in the marketplace.

Discussion

As industries with high risk environments, like construction, manufacturing, or healthcare, are applying machine learning (ML) to employee safety compliance, they are being revolutionised. Proactive safety measures are enabled by predictive models and real time monitoring systems which minimise accidents and increase adherence. Data analysis in form of historical data, worker behaviour and environmental condition can be used machine learning techniques such as decision trees, neural networks, deep learning to help in predicting workplace risks (Coglianese and Lehr, 2016). Along with IoT sensors and wearables, technologies for continuous data allowing for realtime compliance monitoring exist as well. Nevertheless, there remain challenges, such as the problem of model interpretability, data privacy management, and ethical problems. Eventually machine learning will continue to evolve and advancements in explainable AI and automation will progress safety outcomes without sacrificing transparency or fairness. (Rabbi, A. B. K., & Jeelani, I. 2024)

Future Directions

Future work in machine learning for employee safety compliance is likely to centre on how to increase model interpretability and transparency. Expect techniques such as Explainable AI (XAI) to allow decision makers to better understand model predictions so that safety managers can appropriately act on recommendations (Bahr, 2015). Additionally, the adaptation of advanced AI models in AI, like reinforcement learning and deep learning, can enable the generation of more adaptive systems to have in real time the capacity to detect complex safety risks. With the increasing usage of IoT devices, drones, and real time monitoring, data sources will expand creating more precise predictions. However, machine learning can also be combined with augmented reality (AR) and virtual reality (VR) to increase training and simulation programmes, providing a unique immersive safety experience in dangerous workspaces.

Conclusion

As with other industries, machine learning has proved to be an extremely strong tool in improving employee safety compliance, especially with high risk industries. With the aid of predictive analytics, real time monitoring, and automated systems, the ML models can determine and prevent the risk the safety. In addition to predicting potential hazard; these technologies facilitate real time interventions by monitoring continuously to create a safer society. The challenges of interpretable AI and ethics are still there, but methodology within the field of Explainable AI (XAI) and elsewhere are overcoming these issues. Further integration of ML with IoT, wearable sensors, and real time data monitoring will only further improve safety management systems. Now as industries continue to embrace these innovations, accidents will lessen and eliminate, and the current culture of reactive risk management will be less and less.

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