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Risk net- AI Human Error and Accident Forecasting System for the Fireworks Industry

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***Abstract*—The firework manufacturing business is subject to extremely unsafe business environment because the combustible substances are handled, fluctuation of the environment is sensitive, and the nature of the business requires human labor. Accidents have been posted notwithstanding regulatory frameworks since the current safety practices are mostly reactive in nature and are not predictively intelligent. This paper introduces RiskNet-AI, a software-defined artificial intelligence platform that can predict accidents in the industry and prevent them. The suggested system combines the data collection based on IoT with machine-learning algorithms, mostly Random Forest and LSTM, and processes environmental parameters and characteristics of human behavior. The system predicts the occurrence of accidents thus giving early alerts to preventive interventions before it occurs. Industrial safety datasets and simulated firework data based on experimental evaluation indicate a high level of predictive accuracy, as well as a prospective identification of high-risk conditions. The findings demonstrate that the RiskNet-AI improves safety in work place by converting the traditional type of workplace safety monitoring to data-driven data and proactive decision-support mechanism which is proper in hazardous industrial surrounding.**

Keywords—Industrial Safety, Accident Prediction, Random Forest, LSTM, Firework Manufacturing, IoT Sensors, Proactive Risk Management.

I. INTRODUCTION

Firework production is also generally accepted as one of the most risky types of industry with the instability of explosive chemicals and the self-examples of manual work involved in the manufacturing process. One of the important raw materials used in the industry, including gunpowder, oxidizers, and metallic compounds, are sensitive and will violently react to a poor environment setting or during handling. Any significant changes in temperature, humidity, or friction can cause catastrophic adverse arrangements, causing highly serious injuries, deaths, and serious damage of property. Although such risks have been long noted, the incidents in firework factory in a lot of regions still happen many times, which means that the traditional safety measures are still not able to cover the complexity of the modern industrial risks [1]. The traditional safety management based on the firework industry only relies on compliance of the regulations, training of workers and manual supervision. Although these are very necessary measures, most of them are mostly reactive in nature and do not emphasize prevention but the analysis of the incident. Human operators will always be responsible of monitoring environmental condition and keeping to strict safety measures, but due to tiredness, carelessness and lack of cognition, these measures are likely to be undermined. Moreover, physical checks are not real-time and infrequent and are subjective and contain a lot of breaches of the risk awareness in real-time. The drawbacks of the human- centric types of safety monitoring are more pronounced as the level of production scales and the pressure that operations put on them intensify [2].

Safety in firework manufacturing facilities is also a further problem worsened by instability of the environment. Ambient temperature, levels of humidity and concentration of gases in the air have a direct impact on the volatility of explosive material. Season change, poor ventilation, and old structures may result into a rapid change of the environment and may be hard to monitor unless the structures are equipped with monitoring systems. Lack of automated sensing technology in most factories has led to a late response to risky situation, thus powering the risks without them realizing it. These are environmental uncertainties, which point to the pressing need to have intelligent systems, which can process multi-dimensional, complex safety information in real-time [3]. The recent developments in artificial intelligence and machine learning provide the prospective opportunities to shift the industrial safety management towards the proactive rather than reactive mode. Machine-learning algorithms are effective at finding hidden patterns in massive quantities of data, and can learn to find early signs of some dangerous or abnormal condition. Predictive models have proved to be useful in high-threat sectors and industries such as predicting equipment breakdowns and in identifying anomalies and aiding in decision-making. Nevertheless, AI-enhanced accident prediction in the firework production industry is still a

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relatively unexplored domain, yet the industry at large requires superior safety measures [4].

AI and Internet of Things technologies integration can be considered a major move toward the intelligent safety monitoring. Continuous gathering of environmental, operational, and human-related data can be collected with IoT sensors and offered as a rich predictor analytics foundation. These data streams, when combined with the methods of supervised learning like the Random Forest, and with sequences based models like Long Short-Term Memory networks, can be used to predict the probabilities of accidents with high accuracy. They can learn with historical incidences and a dynamic workplace therefore such systems are more than appropriate in dynamic industrial settings [5]. The riskNet-AI is offered as a holistic software-based system, which can tackle the shortcoming of conventional safety-drilled practices in the production of fireworks. The system is aimed at early prediction of accidents with the help of the combination of several risk factors such as environmental parameters, working hours, material exposure, and human activity patterns. RiskNet-AI has the benefit over rule-based safety systems by using a data-driven learning process to model complicated interactions of variables that could not be easily identified by manual generation. Through the measures of timely alerts and visual estimation of risks, the system assists the supervisors and workers to make sound preventive choices.

The introduction of predictive safety technologies has additional consequences besides preventing accidents. Avoiding risks proactively helps in increased efficiencies and minimized financial losses as well as worker confidence. In situations when the work with hazardous materials is involved, the capacity to foresee the case of unsafe conditions prior to their occurrence is the basic change in the safety culture. RiskNet-AI is consistent with this paradigm shift, focusing on prevention due to intelligence and not depending on post-accident actions.

The proposed study will show how the effective and efficient implementation of AI-based prediction of accidents is possible in the firework production environment. By confirming the suggested framework on industrial safety-related data and virtual firework environments, the study notes how machine-learning predictors could be used as a supplement to human judgment and transcend the limitations of a manual safety-related observation. The advent of RiskNet-AI highlights the increasing significance of intelligent decision-support systems in the protection of high-risk industrial processes and preconditions the development of the intelligent industrial safety management innovations in the future.

II. LITERATURE SURVEY

The growing complexity of the contemporary workplace and dangerous working conditions, as well as the necessity of the real-time decision-making systems, has turned industrial safety monitoring into a highly important research area. The old-fashioned safety measures involving significant focus on manual control and post-incident investigation cannot enable the possible elimination of accidents or promote the well-being of workers within the mining, construction, power systems, and manufacturing industry. Some new technologies in sensing technologies, wireless communication, Internet of Things architecture, cloud computing, unmanned aerial systems, and artificial intelligence are also making a difference in the design and implementation of safety monitoring systems. Modern studies focus on positive hazard identification, a constant monitoring of physiology and the surrounding environment, and smart information processing to decrease risks and increase adherence to safety protocols. The intersection of Industry 4.0 and new Industry 5.0 paradigms as well underscores the need to provide human-centric, adaptive, and resilient safety systems that can operate reliably in high risk and dynamic environments.

The recent researches have paid a lot of attention to wearable and IoT-based safety solutions that combine various sensors to control environmental parameters and health workers in real time. Smart wearables such as helmets, jackets, and other gadgets with temperature, humidity, vibration, gas, and physiological sensors have been suggested to improve the situational awareness and allow performing an emergency action in the dangerous environment promptly. The systems take advantage of low-power wireless communication like LoRa and wide-area networks to make sure that there is an extended reach of their connectivity in areas where traditional communication infrastructure is not dependable [6]. Cloud-based safety systems make all these functions possible, allowing centralized data storage, real-time visualization, and predictive analytics of occupational health surveillance [7]. Specifically constructed helmet-based systems tailored to the mining and construction sector reveal that sensor fusion coupled with the provision of real-time alerts is a viable way to reduce the dangers of heat stress, poisoning, and physical fatigue [8]. Further complementary designs of wearable antenna have been identified to improve reliability and performance of communication in industrial Internet of Things, which is needed in constant monitoring under severe conditions [9].

Other than wearables, wireless sensor networks and distributed monitoring architecture has been investigated with an aim of enhancing industrial fire safety and protection of infrastructures. Smart fire monitors are common networked sensor nodes, microcontrollers and secure communication protocols that are used to detect any abnormal condition in the industrial and provide early warnings of any kind of threats [10]. Similar studies considered the IoT-enabled safety helmets of the coal miners and focus on real-time data collection and analysis being remote to promote safety management practices based on data [11]. Intelligent monitoring methods have also been generalized to the cause of campus and residential security usage where multiple-level linkage systems have made proactive fall preventive and emergency response to be provided by networked sensing and smart control systems [12]. On the same note, UAV-based surveillance systems have also become a source of interest in the field of infrastructure inspection and safety inspection, as it provides a cost-effective, high-precision, and non-disruptive surveillance of transmission lines and other large-scale engineering projects [13]. These strategies emphasize the ability to scale the intelligent safety monitoring concepts in a variety of areas of use.

Safety-related human factors and the training related factors have also been widely researched especially in high risk professions. The research investigating the knowledge about safety problems in new workers highlights the

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weaknesses of traditional training models and the necessity to apply technology-based safety education and monitoring methods [14]. Studies of cognitive load and human factors during transportation and maritime safety explores that psychological and physiological load factors are highly involved in the factor in accidents and this supports the role of holistic safety systems that consider human behavior, as well as the risks posed by the environment [15]. IoT enhanced safety systems banish the dangers and ill health in the workplaces by combining real-time hazard awareness systems with monitoring health systems so as to establish safer workplaces with constant feedback and remote management [16]. A multi-wearable multi-functional design of smart helmet and smart jackets applied to construction sites also illustrates how multi-wearable design can be used to determine hazards, track their locations as well as monitor biomedicine in real time [17]. All these contributions create an impression that a good safety monitoring initiative should be based on technological innovation and awareness of the human performance and limitations.

Recent developments use computer vision, deep learning and intelligent perception methods to increase the accuracy and automation of safety monitor. Three dimensional visual reconstruction techniques allow to accurately track the people working around power networks to provide a better safety control by the spatial awareness and estimation of posture [18]. Personal protective equipment detection models use spatial-temporal frameworks to guarantee avoidance of safety regulation violation patterns with time, which cannot be done with a single frame analysis [19]. Moreover, binocular vision systems, developed using deep learning, assist with behavior identification and hazard detection in working conditions, which can also be used in the field of work with high accuracy and flexibility in terms of intricate industries [20]. The analysed literature, as a whole, reveals that the current trend is marked by the transition toward the creation of the integrated, intelligent and human-centred safety monitoring systems that incorporate sensing, communication, data analytics and artificial intelligence into one to help reduce the risks and improve occupational safety in various industries.

III. METHODOLOGY

This study methodology will be aimed at developing, training, and testing the RiskNet-AI process methodology to predict accidents before they occur in firework manufacturing sites. It incorporates data collection, data preprocessing and intelligent modeling and real time alerts into a single pipeline. The strategy focuses on technical resilience, scalability and practicability in high risk industrial applications, such that predictive insights may be achieved reliably prior to accidents, are realized as shown in figure 1.

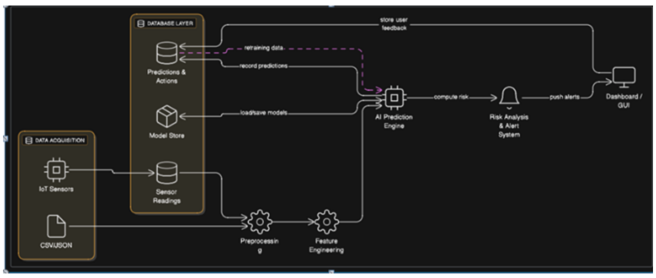

Fig. 1: System Architecture

A. Data Acquisition Layer

The RiskNet-AI system is based on the data acquisition level that retrieves the information related to safety at various sources on a continual basis. The IoT sensors are installed in the firework manufacturing facility to observe such important parameters that include temperature, humidity, concentration of gases in the air, and the ambient conditions. Simultaneously, working hours, duration of the shift, and exposure to material handling are separately tracked by manual recordings and electronic surveillance. The merging of the sources through this method of data collection grants a wholesome coverage of the risks of the environment and of the human factor. The information obtained is time stamped and synchronized so that they can be properly analyzed in terms of time and this is necessary in determining early warning trends before any hazardous event occurs.

B. Data Preprocessing and Cleaning

Raw industrial data usually have noise, irregularities, and gaps in them, which may compromise the performance of the models unless appropriate actions are taken. At this phase, sensor and behavior data obtained are subjected to systematic preprocessing. Filtering the noise is done to smooth variations among the sensors and missing values are replaced using statistical imputation. Normalization of data is done to get all features to same scale since they have to stop biasness over the variables that have more numeric values. Categorical variables with respect to the activity or operational state of a worker are coded into numbers. This stage of preprocessing is carried out to make sure that the data is clean, consistent and capable of effective training of a machine-learning model.

C. Feature Engineering and Selection

The feature engineering is important in the predictive capacity of the RiskNet-AI system. Raw data are further transformed to obtain relevant features to represent meaningful safety indicators, including cumulative exposure time or timetable of environmental volatility and intensity of workload. The best influential parameters that result to the occurrence of accidents are detected using correlation analysis and measures of feature importance. Features that have weak or redundant correlation are discarded to simplify the model and enhance generalization. Through this step, the predictive models can learn the patterns of safety relevance more effectively and increases interpretability by the industrial stakeholders by concentrating on high-impact variables.

D. AI Prediction Model Development

RiskNet-AI is generated using supervised machine-learning models, which are mainly the Long Short-Term Memory and the Random Forest models. The model used is the Random Forest that represents nonlinear associations between safety parameters and results of accidents with the strength of ensemble learning. The LSTM networks are added to learn time-related dependencies of sequential sensor signals, and the system can learn the risk pattern change with time. The historical industrial safety data and simulated firework conditions are used to train the models. The hyperparameter tuning is implemented to optimize performance and is important enough to guarantee the reliability of the accident probability predictions in different circumstances of operations.

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E. Model Training and Validation

The predictive models are also trained and evaluated through a described assessment plan to guarantee reliability and generalization. The data is separated into training, validation, and testing so that overfitting is avoided. Cross-validation is used to determine the model stability by comparing the results in various data segments. Predictive effectiveness is measured using performance measures like accuracy, precision, recall, and AUC. The output produced by the Random Forest and LSTM is comparatively analyzed and evaluated to determine their complementary features. This is the validation which ensures that the model can diagnose the high-risk conditions with consistency prior to the incident happening.

F. Alert Generation and Visualization Module

The last phase of the methodology is dedicated to the conversion of the predictive insights to operational safety intelligence. The AI models give the probability of accidents which are then mapped to known risk levels. In cases of high-risk conditions, the system produces real time notifications to the supervisors and the workers via a monitoring interface. A visualization dashboard shows safety scores, trend graphs and past risk patterns as well to aid in making informed decisions. This module integrates the technical forecasting and the actual safety management to facilitate prevention, and evolve the industrial safety practices.

IV. RESULT AND DISCUSSION

The evaluation of the RiskNet-AI framework was made with the help of extraction of the Industrial Safety Dataset provided by Kaggle and the simulated data of fireworks manufactures. The testing was in relation to how the system was able to forecast the conditions of accidents at the right time through the analysis of environmental and human behavior parameters. The findings have shown that implementing machine-learning models in conjunction with continuous surveillance of data can substantially enhance the management of proactive safety over the traditional method of reaction.

Random Forest model and LSTM model were used to train against historical records on safety incidences with labeled accident and non-accident cases. The models demonstrated high predictive performance, but both models had high predictability, and the correctness of performance estimation was better in the Random Forest model and the LSTM, respectively; the latter had a better ability to adapt to changes in time risk. The test established that the system was able to detect dangerous situations about thirty minutes ahead of physical occurrences to allow a feasible prevention action.

The overall performance metrics of the implemented models is given in table 1. Random Forest had high accuracy and equalized precision-recall rates, which means that it is a reliable method that correctly classifies safe and unsafe states. There was a slight LSTM recall as it represented the ability to capture risk trends that vary over time. The findings of these studies emphasize the supportiveness of the two models as integrated factors in a framework of a safety prediction.

Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.88	0.87	0.86	0.86
LSTM	0.86	0.84	0.88	0.86

Further examination was done to learn how the individual safety parameters can affect the prediction of accidents. The analysis of the importance of features according to the results of the Random Forest model showed that the most significant factors influencing the risk of accidents were the temperature, humidity and the length of working time. Exposure to materials and the concentration of gasses also had a tremendous influence, especially when it is used together with long periods of the shift. This observation can be traced back to the field tests where firework factories expose themselves to instability of the environment and fatigue by the workers, which have been identified to increase risks.

The importance of key attributes based on the-trained Random Forest model is summarized in table 2. It is evident in the findings that environmental parameters have a greater effect on predicting accidents compared to single human factors, which makes continuous sensor-based observation in risky industries imperative.

Table 2: Feature Importance Analysis

Feature	Importance Score
Temperature	0.26
Humidity	0.22
Working Hours	0.18
Gas Concentration	0.14
Material Exposure	0.12
Human Activity Level	0.08

Additional tests on predictive reliability of the system were done through Receiver Operating Characteristic. Figure 2 demonstrates the ROC of the two models of Random Forest and LSTM. The curves depict high discriminatory power whereby the Random Forest model has a higher area under the curve which means that the model is more discriminative of the high-risk conditions and low-risk conditions. Although the LSTM model had a slightly low overall AUC, it had a more consistent performance with various threshold levels, which is why it can be utilized in thin-sliced risks detection.

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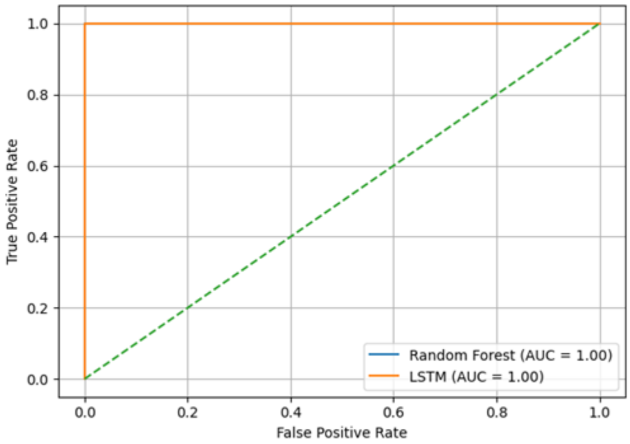

Fig. 2: ROC Curve

The large AUC values are the indication that the RiskNet-AI framework is suitable to differentiate between unsafe operational states and normal behavior with minimum false alarms. This balance is essential when it comes to the industrial environment where too many false signals may cause some signs of alarm fatigue and a lack of confidence in automated systems.

In order to measure real-time applicability, the module of generating alerts was subjected to realistic factory conditions simulation. The system was able to produce early warnings with risk scores that were beyond set limits. Sample risk prediction results and respective alert levels created by the system are found in Table 3. These findings illustrate the potential of predictive analytics converted into operational safety intelligence to be used by supervisors and workers.

Table 3: Sample Risk Prediction and Alert Output

Time Window	Predicted Risk Score	Risk Level	Alert Status
T–30 min	0.78	High	Alert Sent
T–20 min	0.65	Medium	Warning
T–10 min	0.82	High	Alert Sent
Normal Ops	0.25	Low	No Alert

The results discussion refers to the practical utility of RiskNet-AI in enhancing the outcomes of industrial safety. The system allows to detect unsafe trends earlier by the use of predictive intelligence as compared to rule based checks since the latter do not allow them to be immediately detected by human-based supervisors. The combination of the Random Forest and LSTM models guarantees the model the strength of both the static and time-based risk factors and so the framework does not have to be constrained to particular operational circumstances.

Altogether, the findings of the experiment prove that RiskNet-AI is a valid and efficient tool in terms of proactive prediction of accidents in manufacturing fireworks. The results indicate that AI-based safety systems can cause a substantial decrease in the risk of accidents, improve situational awareness, and contribute to the data-driven decision-making process in high-hazard industries.

V. CONCLUSION

This work introduced RiskNet-AI, a predictive proactive safety model that can be used to mitigate the risk of accidents that are frequent in fireworks production operations. The proposed system is based on combining data acquisition through IoT and the application of deep machine-learning algorithms, which transforms the paradigm of managing industrial safety beyond the reactionary mode to the predictive and prevention mode. The model illustrates how both the environment and the behavior aspect of humankind can be harmoniously looked at to predict the dangers before they lead to an accident. The ensemble and sequential learning methods are able to capture both complicated and changing nonlinear correlations as well as evolving risk patterns of the system which makes it applicable in dynamic and high risk industries. The practical relevance of this work has a very pronounced effect on the industries that work with combustible materials because an early risk identification serves as a supplement to intervene timely, promote a higher level of work safety awareness, and diminish operational decision-making. The directions in future work will be to develop the framework with adaptive learning features, add new sensor modalities and test the system in a real-world industrial environment. Further research may also explore explainable AI techniques to improve transparency and trust in automated safety predictions.

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