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Intelligent Factory Safety and Emergency Response System Using LabVIEW

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Abstract

The main goal of this study is to develop an intelligent factory safety and emergency response system using IoT, Machine Learning, and LabVIEW ensuring industrial safety requires continuous monitoring of critical parameters such as vibration, temperature, humidity, and sound. Manual monitoring is inefficient and prone to errors. This system employs real-time sensor data acquisition, anomaly detection using machine learning, and trend analysis for predictive maintenance. Sensor data is logged into Firebase and Google Sheet, training the ML model using the data from the google sheets, enabling visualization in LabVIEW. The system analyzes the past 5 minutes, current sensor data, and forecasts the next 5 minutes to ensure timely prediction. In addition to visualization, the system includes an automated alert mechanism that sends SMS notifications to designated personnel whenever an anomaly is detected, ensuring immediate response to potential hazards. Safety mechanisms such as relay-based emergency shutdowns can be triggered automatically to prevent catastrophic failures. By integrating real-time anomaly detection, predictive maintenance, and automated emergency response, this system enhances industrial safety, improves operational efficiency, and minimizes unplanned downtime. The proposed approach ensures a proactive, data-driven strategy for factory safety management, reducing risks and optimizing industrial processes.

Keywords: *Machine Learning, Prophet, LabVIEW, Anomaly Detection, Predictive Maintenance.*

1. Introduction

Industrial safety has become more important than ever with the rise of automation and heavy machinery in modern factories. As systems grow more complex, real-time monitoring is essential to avoid accidents and equipment failures. Shockingly, reports from the International Labour Organization (ILO) reveal that around 2.3 million workers lose their lives each year due to work-related incidents—many of which are tied to machine malfunctions. Studies also show that over 70% of these accidents are caused by delayed maintenance or failure detection. To solve this, industries are turning to technologies like the Internet of Things (IoT) and Machine Learning (ML). Predictive maintenance powered by these tools can reduce unexpected failures by up to 55% and cut maintenance costs by about 30%. Monitoring key factors like temperature, vibration, humidity, and sound in real time helps prevent serious breakdowns. Still, traditional monitoring methods often miss warning signs, leading to around 20% more downtime. This project introduces an Intelligent Factory Safety and Emergency Response System built using IoT, ML, and LabVIEW. It captures live sensor data, detects anomalies, and analyzes trends by studying past and current readings to forecast future risks. When something unusual is detected, the system sends out instant alerts. All predictions and warnings are stored in Firebase and Google Sheets and shown visually through LabVIEW.What makes the system even more effective is its automated SMS alert feature, which immediately notifies workers of any critical issues. Research suggests that predictive safety systems like this can improve workplace safety by up to 40% and reduce emergency repair costs by 25%. With faster alerts and accurate predictions, the

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system aims to reduce downtime and prevent serious industrial accidents.

2. Literature Survey

Ricardo Reyes-Acosta et al. [1] conducted a detailed review on the use of machine learning techniques to enhance the security of IoT systems in smart industries. Their work examines various ML-based strategies and highlights how these technologies can effectively address cybersecurity threats, making IIoT environments more secure and resilient. Jeba Emilyn J. and her team [2] presented a deep learning-based solution for predictive maintenance in Industrial IoT applications. Their research focuses on how deep learning can be leveraged to anticipate equipment failures in advance, improving safety and reducing downtime in industrial settings through continuous monitoring and intelligent decision-making. Aaryan Suthar and co-authors [3] proposed a model that combines real-time monitoring and predictive maintenance using IoT and cloud computing. Their approach demonstrates how continuous sensor data collection and analysis can help detect irregularities early, ensuring a safer and more efficient industrial operation. Akhilesh Kota [4] explored the integration of edge AI and cloud computing for predictive maintenance in IIoT. The study highlights the advantages of using edge devices to process data locally and respond faster, while cloud infrastructure supports long-term analytics and storage, ultimately contributing to smarter and quicker decision-making in industrial safety management [5].

3. Existing Method

In today's industrial settings, ensuring safety and quick emergency response is essential [6]. Traditional systems often depend on manual checks and reactive methods, which can delay action and increase the chance of accidents. Most factories still use basic tools like scheduled inspections, CCTV, and separate alarm systems that don't offer real-time monitoring or predictive insights. Often, workers have to report issues themselves—like unusual vibrations, gas leaks, or temperature spikes—which can be dangerous if missed. These safety systems also tend to work in isolation, without a unified platform to collect and analyze data. This leads to gaps in safety procedures and slower decision-making during emergencies. Without real-time anomaly detection and integration with modern IoT or AI technologies, preventing incidents before they happen remains a major challenge [7-9].

4. Proposed Method

In this system, an Intelligent Factory Safety and Emergency Response System is developed to ensure real-time hazard detection and predictive maintenance in industrial environments. The system continuously monitors key safety parameters, including temperature, vibration, and sound levels, using sensors of the past data and predicts the data of the next 5 min [10]. If any parameter trend is abnormal in the future prediction the system triggers automated safety measures, such as motor shutdown, alarm activation, and sending emergency notifications e.g., SMS to the personnel. To achieve accurate anomaly detection, the system utilizes Machine Learning (ML) algorithms, specifically prophet algorithm, to identify abnormal patterns in sensor data over trends. The LabVIEW interface is integrated with Google Firebase and Google Sheets, allowing real-time visualization and historical trend analysis. The ML model predicts potential safety risks by analysing past sensor data, current readings, and forecasting short-term future trends (Figure 1).

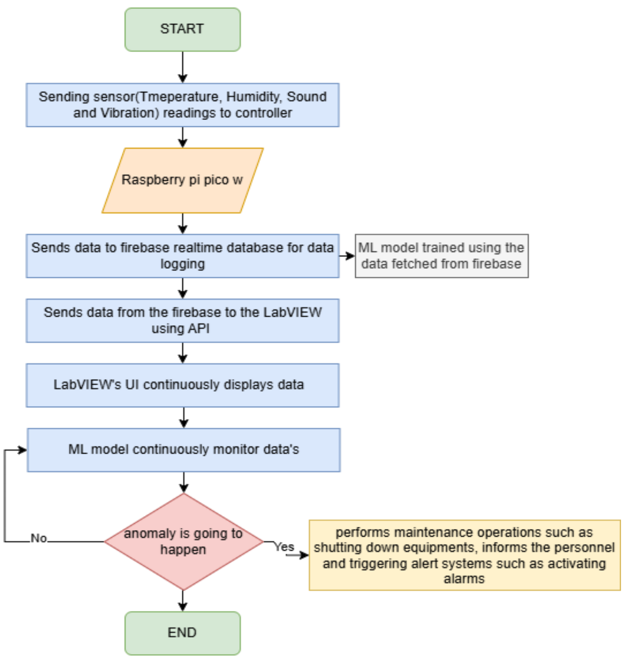

Figure 1 Flow Diagram of the Proposed Method

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This system follows different methods , they are

4.1.Sensor Data Acquisition

Sensors continuously collect temperature, humidity, vibration, and sound intensity data (Figure 2).

- DHT11 → Measures temperature and humidity
- Vibration Sensor → Detects mechanical instability or abnormal vibrations
- Sound Sensor → Captures unusual noise levels in the factory

The Raspberry Pi Pico W fetches real-time readings and logs them into Google Firebase and Google Sheets every 5 seconds. Then these data are ready to fed the ML model training [11].

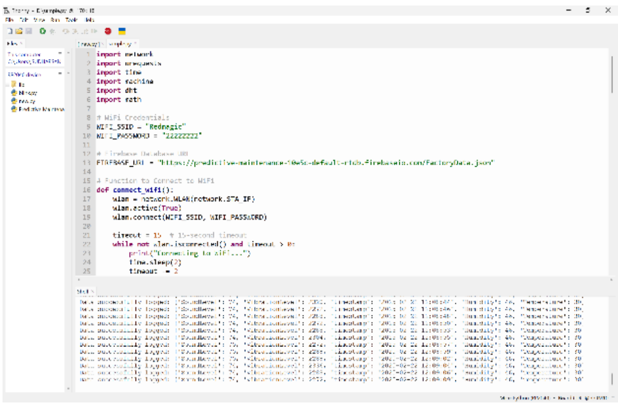

Figure 2 Sensor Data Acquisition

4.2.Preprocessing and Normalization

To improve anomaly detection and forecasting accuracy, sensor data is preprocessed for Prophet analysis. Missing values are handled using forward fill to maintain time-series continuity, and the data is downsampled to 5-second intervals to reduce memory usage while preserving trends. Noise is reduced using moving averages and outlier removal, allowing Prophet to capture both long-term and short-term patterns effectively. Timestamps are converted to a readable format, and Prophet automatically detects seasonality, trend shifts, and anomalies [12]. These steps ensure the data is clean and structured for accurate predictive analysis and timely threat detection.

4.3.Real-time Monitoring and Logging

The system stores sensor data in Firebase Realtime Database, ensuring Continuous data logging (every 5 seconds), Historical data retrieval for trend analysis, Remote monitoring via Google Sheets & LabVIEW. The Google spreadsheets for the past and future are updated dynamically, displaying past trends and predicting the next 5 minutes of sensor behavior. This allows factory personnel to monitor hazards remotely and take preventive actions before failures occur (Figure 3).

A1 | fx Timestamp

	A	B	C	D	E
1	Timestamp	Temperature	Humidity	SoundLevel	VibrationLevel
2	2025-03-13 16:00:02	30.0	47.0	72.0	2352.0
3	2025-03-13 16:00:06	30.0	47.0	72.0	2176.0
4	2025-03-13 16:00:11	30.0	47.0	72.0	2320.0
5	2025-03-13 16:00:20	30.0	47.0	72.0	2320.0
6	2025-03-13 16:00:25	30.0	47.0	72.0	2320.0
7	2025-03-13 16:00:29	30.0	47.0	72.0	2336.0
8	2025-03-13 16:00:37	30.0	47.0	72.0	2336.0
9	2025-03-13 16:00:42	30.0	47.0	72.0	2304.0
10	2025-03-13 16:00:49	30.0	47.0	73.0	2240.0
11	2025-03-13 16:00:54	30.0	47.0	73.0	2272.0
12	2025-03-13 16:00:59	30.0	47.0	72.0	2288.0
13	2025-03-13 16:01:06	30.0	47.0	72.0	2304.0

Figure 3 Real-Time Sensor Data Logging in Google Sheets

4.4.Anomaly Detection using ML

The system uses the Prophet model to analyze past sensor data (temperature, humidity, vibration, and sound) and forecast trends for the next 5 minutes. Predicted values are compared with normal ranges, and significant deviations are flagged as anomalies, triggering safety alerts. The model also detects trend shifts and seasonal patterns to anticipate failures. By leveraging Prophet’s forecasting and anomaly detection, the system improves industrial safety through real-time monitoring and early warnings [13].

Prophet model: Prophet is a time series forecasting model developed by Facebook (Meta), designed to handle missing data, outliers, and seasonal variations. It's widely used in business and industrial settings for tasks like sales forecasting, predictive maintenance, and anomaly detection. The model starts with historical data—such as power load or temperature—and preprocesses it by handling missing values, outliers, and seasonal trends. Prophet breaks time series into three main components: Prophet models time series data as the sum of three components:

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$$\mathbf{y(t)=g(t)+s(t)+h(t)+\epsilon t}$$

Where:

g(t) → Trend (long-term changes in data)
s(t) → Seasonal variation (recurring patterns)
h(t) → Holiday effects (special event impacts)
ϵt → Noise (random fluctuations)

Prophet uses an additive regression approach, modelling each component separately and combining them to generate accurate forecasts (Figure 4). [14] Though simpler than deep learning models, Prophet follows a similar decomposition principle for time series prediction.

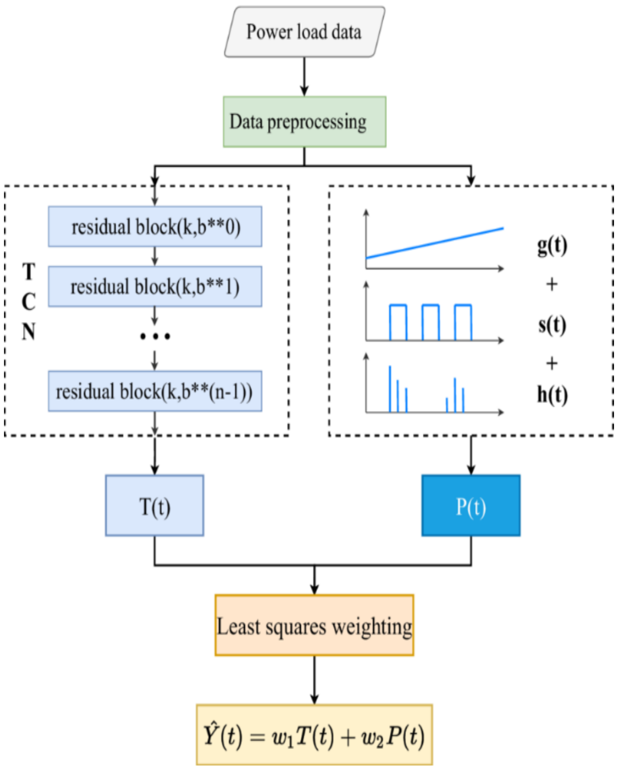

Figure 4 Prophet Model Framework

Model training and evaluation: The Prophet model is trained on historical sensor data, split into training (70%), validation (20%), and testing (10%) sets. It identifies trends, seasonality, and external factors affecting readings [15]. Prophet automatically fits additive or multiplicative seasonality based on the data. Key hyperparameters like changepoint_prior_scale and seasonality mode are tuned to improve accuracy. To assess model performance, the following metrics are used:

- Root Mean Squared Error (RMSE) – Measures the difference between actual and predicted values, giving higher weight to large errors.

  $$RMSE = 1/n1\sqrt{\sum(yactual - ypredicted)2}$$

- Mean Absolute Error (MAE) – Provides an average of absolute errors to evaluate overall prediction accuracy.

  $$MAE = n1\sum \mid yactual - ypredicted \mid$$

- Mean Absolute Percentage Error (MAPE) – Expresses forecast accuracy as a percentage.

The model's predictions are compared against actual sensor readings from the test dataset to evaluate its effectiveness in detecting anomalies and forecasting future trends.

4.5.Visualization and Analysis

The results are visualized using time-series graphs, where actual vs. predicted values are plotted over time. The model's confidence intervals help identify uncertainty levels in predictions. Below are the plots that represents the model precision and accuracy of how well the model is forecasting the future predictions to the actual values. Refer Figures 5 to 8.

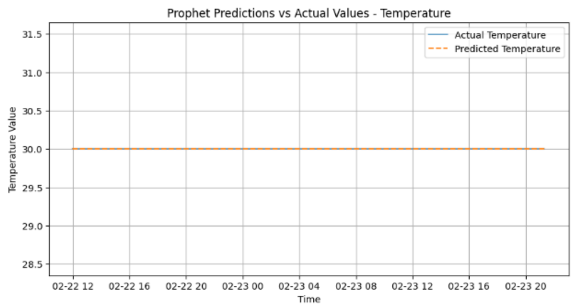

Figure 5 Temperature Visualization

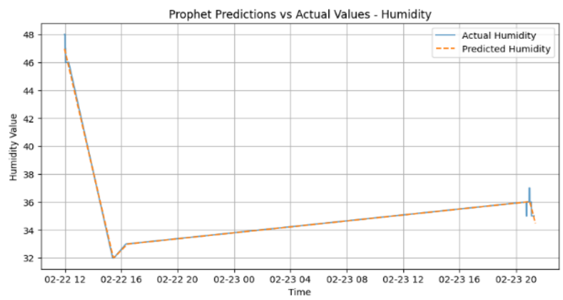

Figure 6 Humidity Visualization

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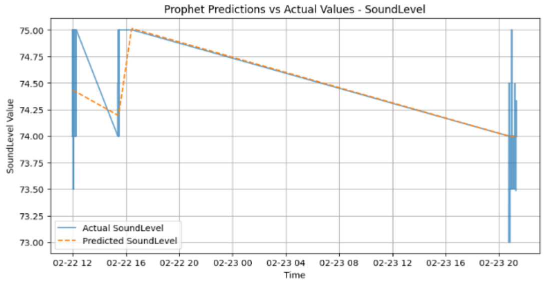

Figure 7 Sound Visualization

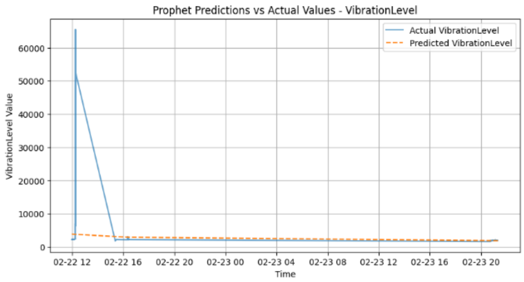

Figure 8 Vibration Visualization

4.6.Alert Generation and Data Visualization

To facilitate real-time monitoring and proactive decision-making, the system generates alerts and provides comprehensive data visualization. Alerts are triggered when the prophet model detects deviations from expected sensor patterns (Table 1). Warning alerts prompt personnel to monitor the situation and trigger emergency notifications via SMS, cloud-based alerts, or alarm systems to ensure immediate attention. The system also features an interactive dashboard that displays historical trends, real-time sensor values, and future predictions. Graphical visualizations, such as time-series plots, anomaly markers, and trend projections, help operators identify emerging issues and assess potential risks. Results are shown in Figures 9 to 17.

5. Results and Discussion

5.1.Results

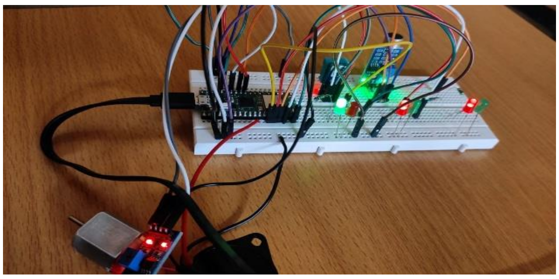

Figure 9 Hardware Setup

Table 1 Overall Metrics of the Trained Prophet Model

Metrics	Value
Mean Absolute Error (MAE)	4.32
Root Mean Squared Error (RMSE)	5.18
R^2 Score	0.994

Figure 10 Real-Time Data Logging in Firebase Database

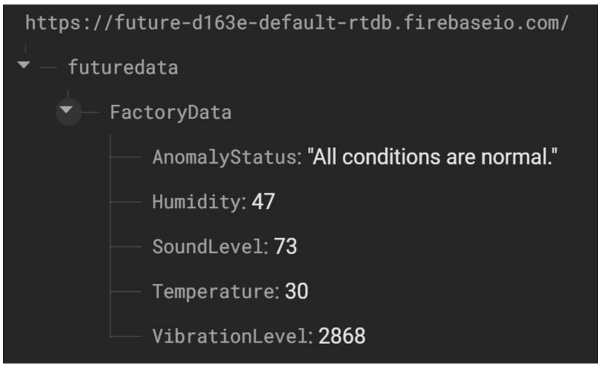

Figure 11 Future Prediction Logging in Firebase (Normal)

Figure 12 Future Prediction Logging in Firebase (Anomaly)

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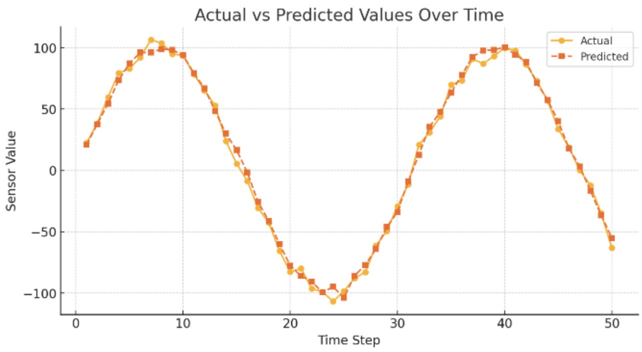

Figure 13 **Ml Graph Plot**

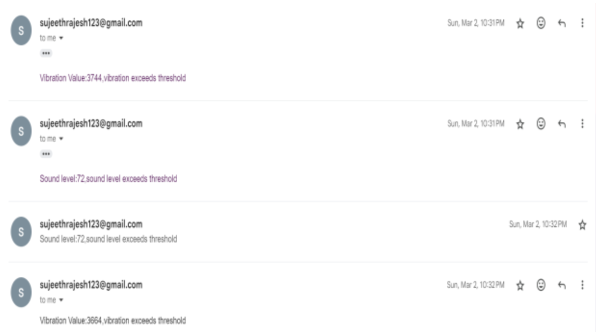

Figure 14 **Email Received Whenever Anomaly Going To Happen**

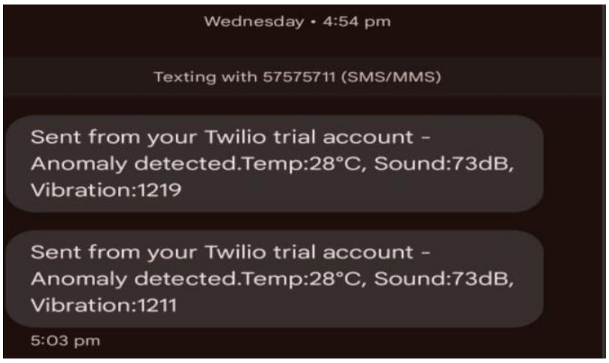

Figure 15 **SMS Sent to The Users Mobile**

Figure 16 **Labview Visualization of Real-Time Data**

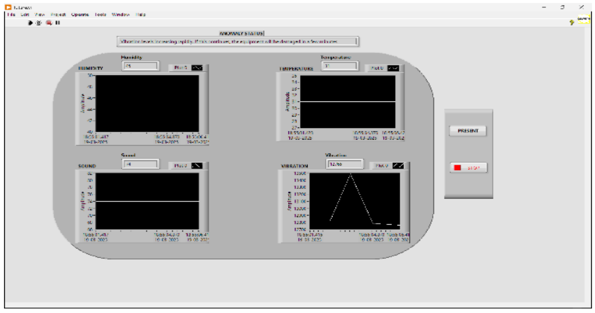

Figure 17 **Lab view Visualization of the Predicted Future 5 Min Trend**

5.2.Discussion

Figure 10. represents the firebase real-time database for logging the current data. Figure 11. and Figure 12. represents the database to store the future trend predicted by the ML model, whereas Figure 11. represents the normal state and Figure 12. represents the event of anomaly going to happen. Figure 13. represents the overall actual vs predicted graph plotted from the results of the ML model which indicates the model is trained well. Table 1. represents the results of the metrics from the trained ML model, where the lower value of the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) indicates minimal deviation between actual and predicted values. Figure 14. and Figure 15. represents the alerts sent to the personnel whenever the anomaly going to happen. Figure 14. represents the email sent to the user through LabVIEW. Since LabVIEW handles most of the process the latency is sending email is about 3-5 seconds compared to the SMS sent through a third-party API which is only 1-2 seconds. Figure 16. represents the VI of the present data logging which has a graph, indicators to alert the personnel. Figure 17. represents the VI of the future where the future 5-minute trend of the parameters is displayed.

Conclusion

In this study, Intelligent factory safety and emergency response system using LabVIEW the system continuously monitors real-time sensor data, analyses trends of the past and present data thereby predicting the future trend, and predicts potential hazards. Through predictive maintenance, the system forecasts equipment failures or unsafe conditions by and sends alerts. When anomalies are detected, it will notify the personnel via SMS, email and through alarm. This automation improves safety and reduces manual checks. A key challenge is sensor noise and data inconsistency, which can impact prediction accuracy. Performance can be enhanced by optimizing sensor placement, applying advanced filters, and using a stronger anomaly detection model. Future improvements include integrating AI-driven prescriptive maintenance to suggest corrective actions based on data and best practices.

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References

[1]. Ricardo Reyes-Acosta, Carlos Dominguez-Baez, Ricardo Mendoza-Gonzalez, Miguel Vargas Martin (2024). Analysis of machine learning-based approaches for securing the Internet of Things in the smart industry: a multivocal state of knowledge review. International Journal of Information Security, 1(24), 1615-5270. doi: 10.1007/s10207-024-00935-8.

[2]. Jeba Emilyn J., Vinod Kumar D., David Samuel Azariya S., Prakash M., Sam Thamburaj A. (2024), Deep Learning-based Predictive Maintenance for Industrial IoT Applications. International Conference on Inventive Computation Technologies (ICICT), 1197-1202. doi: 10.1109/ICICT60155.2024.10544377.

[3]. Aaryan Suthar, Kishor Kolhe, Vitthal Gutte, Dhanashri Patil (2024). Predictive Maintenance and Real Time Monitoring using IoT and Cloud Computing. 5th International Conference on Image Processing and Capsule Networks (ICIPCN). doi: 10.1109/ICIPCN63822.2024.00141.

[4]. Akhilesh Kota, Researcher VII (2024), Predictive Maintenance: Integrating Edge AI with Cloud Computing for Industrial IoT. International Journal of Research in Computer Applications and Information Technology, 7. doi: 10.34218/IJRCAIT_07_02_218.

[5]. Vaibhav Agarwal, Shashikala Tapaswi, Prasenjit Chanak, Neeraj Kumar (2023), Intelligent Emergency Evacuation System for Industrial Environments Using IoT-Enabled WSNs. IEEE Transactions on Instrumentation and Measurement, 72, 1557-9662. doi: 10.1109/TIM.2023.3328071.

[6]. Attila Frankó, Gergely Hollósi, Dániel Ficzere, Pal Varga (2023). Applied Machine Learning for IIoT and Smart Production—Methods to Improve Production Quality, Safety and Sustainability. Sensors, 22(23), 1424-8220. doi: 10.3390/s22239148.

[7]. Angel Jaramillo-Alcazar, Jaime Govea, William Villegas-Ch (2023), Anomaly Detection in a Smart Industrial Machinery Plant Using IoT and Machine Learning. Sensors, 23(19), 1424-8220. doi: 10.3390/s23198286.

[8]. A. Jaya Mabel Rani, B. Yasotha, Sevanthi P, K. Karthika, Y.Alexander Jeevanantham, V.Samuthira Pandi (2023), Predictive Analytics for Proactive Maintenance in Industrial IoT Applications. 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA). doi: 10.1109/ICECA58529.2023.10394792.

[9]. Michele Compare, Piero Baraldi, Enrico Zio (2020), Challenges to IoT-Enabled Predictive Maintenance for Industry 4.0. IEEE Internet of Things Journal, 7(5), 2327-4662. doi: 10.1109/JIOT.2019.2957029.

[10]. Harvey Picot, Muhammad Ateeq, Badr Abdullah, Jeff Cullen (2019), Industry 4.0 LabVIEW Based Industrial Condition Monitoring System for Industrial IoT System. ResearchGate. doi: 10.1109/DeSE.2019.00189.

[11]. Lakshmana Phaneendra Maguluri, Tumma Srinivasarao, Maganti Syamala, R. Ragupathy, N. J. Nalini (2018), Efficient Smart Emergency Response System for Fire Hazards using IoT. International Journal of

Advanced Computer Science and Applications (IJACSA), 9(1), 2156-5570. doi: 10.14569/IJACSA.2018.090143.

[12]. Afsana Khan, Afrida Anzum Aesha, Juthi Sarker Aka, S. M. Faisal Rahman, Md. Jamil-Ur Rahman (2018), An IoT Based Intelligent Fire Evacuation System. 21st International Conference of Computer and Information Technology (ICCIT). doi: 10.1109/ICCITECHN.2018.8631945.

[13]. Ameeth Kanawaday, Aditya Sane (2017), Machine learning for predictive maintenance of industrial machines using IoT sensor data. 8th IEEE International Conference on Software Engineering and Service Science (ICSESS). doi: 10.1109/ICSESS.2017.8342870.

[14]. Md Iftekharul, Abid Ar Rafi, Md Neamul, Md Rifat (2016), An Intelligent Fire Detection and Mitigation System Safe from Fire (SFF). International Journal of Computer Applications, 133. doi: 10.5120/ijca2016907858.

[15]. Mauro Mathias, Everton Coelho de Medeiros, Valdeci Goncalves (2012), Design of a LabVIEW System Applied to Predictive Maintenance. Applied Mechanics and Materials, 249-250. doi: 10.4028/www.scientific.net/AMM.249-250.208.