

## Real-Time Manufacturing Intelligence Through IoT-Integrated ERP Systems

Pavan Kumar Adabala  
Independent Researcher, USA

### Abstract

Predictive maintenance is discussed within manufacturing. The research considers how manufacturing industries apply IoT-enabled ERP systems to predict/prevent machine failure. Through using real-time data from IoT devices, the system can improve its operations, reduce downtime, and facilitate timely decision-making. Predictive maintenance alerts affect production processes in addition to being part of the predictive approach as well. It is evident from this that IoT-ERP systems have been seen to offer some advantages in relation to this matter, while the research faces an issue with class imbalance. The research is still improving the models to make them suitable for analyzing different areas of production, and extending their capabilities as well.

**Keywords:** *IoT Integration, Real-Time Analytics, Predictive Maintenance, ERP Systems, Manufacturing Optimization*

### I. INTRODUCTION

The manufacturing industry can benefit from intelligent IoT ERP systems. These kinds of systems can enhance data visibility, promote automation, and aid in decision-making by integrating sensors, machines, and systems into the ERP system. As a result, efficient processes, improved productivity, and proactive prediction-based maintenance, inventory management, and production can be obtained.

#### **Research Aim and Objectives**

##### **Aim**

The aim at examining IoT-integrated ERP systems in manufacturing, providing live data that improves manufacturing efficiency, enhances decision processes, and streamlines activities.

##### **Objectives**

- To assess the overall impact of the IoT-enabled ERP frameworks on improving real-time data visibility within the manufacturing procedures.
- To examine the role of IoT incorporation on the operational efficiency, along with decision-making within manufacturing contexts.
- To comprehend the advantages of real-time tracking along with predictive maintenance within IoT-ERP frameworks.

- To discuss the issues and solutions for IoT-ERP system integration in manufacturing.

##### **Problem statement**

IoT-enabled ERP frameworks in manufacturing confront issues within real-time data visibility, efficiency, decision-making, and predictive maintenance. Enhanced automation is assessed through IoT, while manufacturing companies confront issues within data integration along with system interoperability, as well as scientific decision-making [1]. The research assesses ways to assess challenges to incorporate IoT-ERP for greater manufacturing intelligence as well as efficiency.

##### **Novel contribution**

The research provides an in-depth understanding of how different positions in practical predictive maintenance, decision-making, and improvised operation efficiency can lead to better productivity. The research uniquely assesses the incorporation of IoT with the ERP frameworks, improving predictive maintenance and also real-time choices within manufacturing. This manages interoperability issues, delivering solutions for adequate data incorporation, enhancing operational efficiency, and modernizing digital transformation within manufacturing procedures.

### II. LITERATURE REVIEW

#### **The Role of IoT-Enabled ERP Systems in Enhancing Real-Time Data Visibility**

Manufacturing greatly depends on IoT-ERP systems for immediate information retrieval. Integration of IoT devices in ERP systems facilitates the collection as well as transmission of data related to the state of affairs in production lines, inventory, and performance indicators of installed machinery [2]. Manufacturers can monitor the temperature, pressure, machine health, and other related factors using real-time data obtained through IoT devices [3]. It improves the availability of data and its correctness, eliminating any danger to life-or-death decisions within a high-speed and dynamic manufacturing environment.

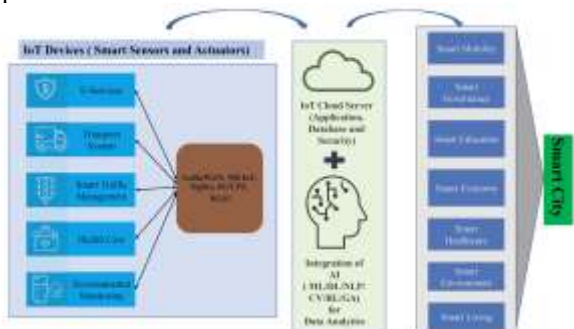


**Fig 1: IoT for greater financial growth**

Resources and assets can be tracked efficiently, wastages eliminated, inventory control improved, and productivity increased using information [4]. Early problem identification is possible for manufacturers. This is through linking devices like machines so that they may quickly react while being on the lookout for any emerging issues. The integration of ERP systems with IoT may offer some information pertaining to manufacturing, starting from buying and ending up under transportation section [5]. Increased visibility assists in proper production scheduling, resource allocation, as well as streamlining of various manufacturing processes to obtain better manufacturing output and being agile at it.

**Impact of IoT Integration on Operational Efficiency and Decision-Making**

The linkage of IoT and ERP systems plays their part in factory efficiency through automation, which minimizes mistakes. The information coming from these devices is seized at the point of origin in the manufacturing machinery and production lines, thereby eliminating manual entry requirements that can lead to mistakes, as explained [6]. Data information is going in real-time, on which analysis can occur, and a state can be taken immediately, adding insight/areas for improving any current process.

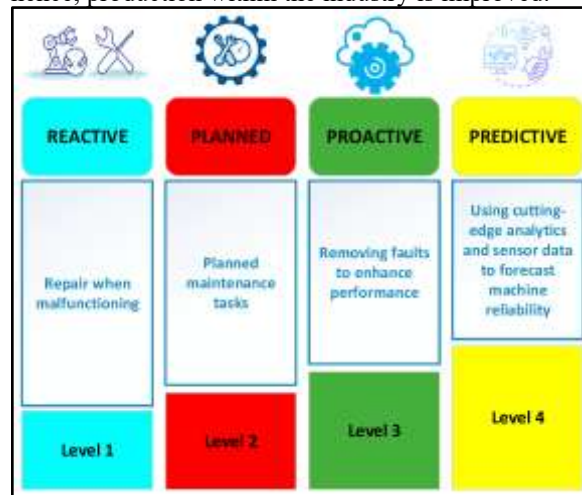


**Fig 2: Incorporation of IoT-Enabled Technologies for Smart City contexts**

Enhanced machinery and accuracy resulted in better operations and wise judgment. Internet of Things sensors offer timely information meant for advancing projections and plans, including inventory controls [7]. IoT sensors can transmit such information to the ERP system that schedules maintenance activities, thus reducing downtime while a machine is about to break down. Information about the usage of machines and the quality or number of products produced can serve in determining the scheduling of processes, as there are no traffic jams and production moves smoothly [8]. This assists in cutting down production costs, optimizing available resources, and increasing revenue.

**Benefits of Real-Time Monitoring and Predictive Maintenance in IoT-ERP Systems**

IoT-driven ERP systems offer the best way of including real-time evaluation as well as predictive maintenance in the manufacturing sector [9]. It is possible to gather data concerning the state of particular machines, performance data, and condition indicators collected from equipment embedded with IoT, such as their age or issues with them, and information on wear and tear. Details can also be perceived by IoT-ERP systems, which analyze them for signs of impending malfunction that may require servicing [10]. There is a kind of servicing that helps in saving on repair costs and avoiding downtimes; hence, production within the industry is improved.



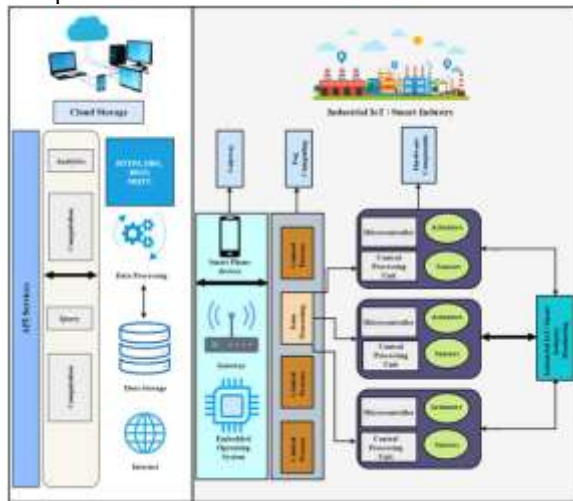
**Fig 3: Artificial Intelligence for Predictive Maintenance Implementations**

In addition, manufacturers can keep quality in check through monitoring. Monitoring the manufacturing process in real time helps identify problems instantly that can be rectified on the spot [11]. This leads to good products, less wastage, and pleased customers.

Internet of Things-integrated ERP systems enhance efficient and effective production processes.

### **Challenges and Solutions in Implementing IoT-Enabled ERP Systems in Manufacturing**

The application of systems in manufacturing plants comes with some difficulties, though these systems are very beneficial. There is one problem that is more visible than others: integrating IoT devices with current ERP systems. Manufacturing plants experience challenges while attempting to update ERP systems that have been operational for numerous years [12]. As a result, this can complicate device integration as well as proper analysis and interpretation of data.



**Fig 4: Role of Industrial IoT within Manufacturing for Implementation**

Manufacturers continuously gather data in order to keep themselves safe from hackers. Manufacturers can ensure that they protect the integrity of their data as it moves from one point of the Internet of Things (IoT) into the Enterprise Resource Planning (ERP) system. Data in the ERP system failure can lead to data breaches and can also expose intellectual properties for theft. In addition, organizations can find it hard to manage voluminous data collected through IoT devices, especially when they lack enough space and personnel to assist them in analyzing information captured by those devices.

Organizations need to have appropriate technologies in place for data storage, processing, and analysis [14]. Manufacturers are required to consider approaches such as using cloud computing-based IoT systems that can be integrated with existing systems, cybersecurity, and the incremental upgrade of ERP systems [15]. Technology and human resources expenditure, and process reengineering can ensure optimal value extraction from the data gathered.

### **Literature gap**

Research into the utilization of IoT-related ERP systems in manufacturing is quite scarce when it comes to applying them for timely data inclusion, so as to boost predictive maintenance and operational efficiency itself [16]. Most previous studies tend to center on one particular technology or even specific case studies alone, leaving aside integration problems, security matters, and indeed, affecting decision-making in different industries.

### **III. METHODOLOGY**

#### **Research Design**

The research has a mixed methods design and uses case studies as well as data analysis. Research on the deployment of IoT-enabled ERP frameworks within manufacturing was developed through discussions with industry experts, evaluating performance data. This process helps find out about problems, advantages, and benefits of much higher efficiency and better decision-making.

#### **Data Collection**

ERP performance data can be collected, involving real-time operational data, maintenance data, and outcomes of decisions made with IoT-enabled ERP frameworks. Patterns, issues, as well as advantages of utilizing the system in manufacturing contexts can be recognized from the data. The dataset for the research is a simulated manufacturing data, involving operational parameters such as “pressure, temperature, humidity, vibration, as well as machine age”. The secondary data is collected and the primary evaluation strategy involves statistical evaluations for examining ERP performance within real-time, involving efficiency metrics and predictive maintenance alerts from the IoT-associated frameworks.

#### **Data Quality Analysis**

Data quality analysis serves a vital role in the success of IoT-enabled ERP frameworks for manufacturing. Real-time data from IoT sensors is gathered for decision-making purposes, as data quality is crucial. Data completeness is determined through examining the complete data from the sensor; incomplete data can affect the reliability of the specific system [17]. The element is consistency, which defines the data from multiple IoT devices. Conflicts in the data, involving different time-stamps or units, can influence real-time operational choices as well as procedures.

Accuracy validity is assessed through comparing the data from the sensors with benchmark data or data gathered manually from other sources, involving maintenance records or manual observations.

$$DQI = \frac{\text{Valid Data Points}}{\text{Total data points}} \times 100$$

The index can be utilized to evaluate the percentage of complete and correct data gathered, and also determine the accuracy of the IoT-enabled ERP framework.

### **System Architecture and Integration**

The integration of IoT-enabled ERP systems in manufacturing uses a multi-tiered architecture, with IoT sensors, devices, and the ERP system communicating in real-time. IoT-enabled ERP systems employ edge computing to locally process and forward data to the ERP system, enhancing data processing efficiency and reducing network traffic [18]. The elements involve IoT sensors for data collection, data protocols involving CoAP and MQTT, along with a cloud or on-premise ERP framework for data storage and processing. IoT devices communicate with the ERP system through middleware, which translates, aggregates, and assures interoperability among systems [19]. Integration considerations involve sensor accuracy, data format conversion, calibration, and scheduling downtimes for ERP and IoT devices.

### **Real-Time Data Analytics and Decision-Making**

Instantaneous details from real-time data analytics in IoT-enabled ERP frameworks allow manufacturers to make decisions in real-time. Sensors on IoT devices are monitored in real-time to recognize patterns, predict device malfunctions, and schedule manufacturing operations [20]. Machine learning approaches involving classification, regression, and time series forecasting are also typically used for predictive analytics to recognize unusual behavior in equipment or manufacturing procedures [21]. This allows for timely interventions to mitigate potential losses. Managers also have access to reports, visual interpretations, “key performance indicators (KPI)”, along with dashboards through the business intelligence (BI) tools linked with an ERP framework. This allows for real-time decision-making based on the current state of the business, resulting in improved productivity as well as resource allocation.

### **Predictive Maintenance and Performance Optimization**

An important use case of an IoT-connected ERP system is predictive maintenance to decrease equipment failure and increase system resilience. IoT senses the status of machinery by measuring factors such as temperature, vibration, and pressure [22]. Insight from this information is generated using statistical approaches, along with machine learning approaches, to forecast machine problems. The ERP system develops maintenance work orders based on expected equipment wear and tear and reduces

unscheduled maintenance [23]. Predictive maintenance allows manufacturers to increase machine lifespan, lower maintenance costs, and enhance machine efficiency [24]. Optimization of IoT-ERP systems also comes from monitoring system performance and identifying inefficient assets to inform decisions around resource allocation and process improvements.

### **Security and Data Privacy in IoT-ERP Systems**

Data security and privacy are paramount to IoT-enabled ERP systems, with the vast amount of confidential data generated from the manufacturing industry [25]. Protocols need to be in place to secure IoT devices from cyber threats and other primary infiltration [26]. These involve the utilizations of encryption standards like TLS or SSL for data transmission from IoT devices to ERP systems. Measures involve utilization of “identity and access management (IAM)” frameworks to control access to key system functions [27]. This is also significant for the ERP framework to develop routine data audits and unusual activity detection. Data privacy is addressed by adhering to data protection regulations such as GDPR, ensuring that, while relevant, personal and other data is deidentified.

### **Data Analysis and Reporting**

IoT ERP systems utilize data analysis and reporting to extract useful details from real-time manufacturing data. Data is preprocessed for cleaning, normalization, and feature extraction, proceeding to statistical analysis and machine learning [28].

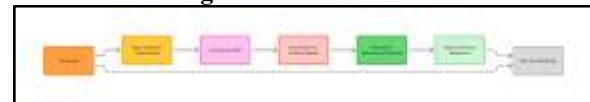
System architecture includes machine learning methods involving “RandomForestClassifier” for predictive maintenance, improving choices by real-time data evaluation within IoT-incorporated ERP frameworks.

“Key performance indicators (KPIs)” like overall equipment effectiveness, machine condition, and inventory levels are measured [29]. A significant metric within reporting is the “Overall Equipment Effectiveness (OEE)”, evaluated as:

$$OEE = \text{Availability} \times \text{Performance} \times \text{Quality}$$

Availability, Performance, and Quality are system measures calculated from IoT data.

### **Architecture diagram**



**Fig 5: System Architecture diagram**

The architecture diagram shows a data stream from IoT to an ERP framework with a focus on real-time monitoring, data preprocessing, predictive modeling,

analytics, performance optimization, and decision-making for manufacturing intelligence.

### Pseudocode

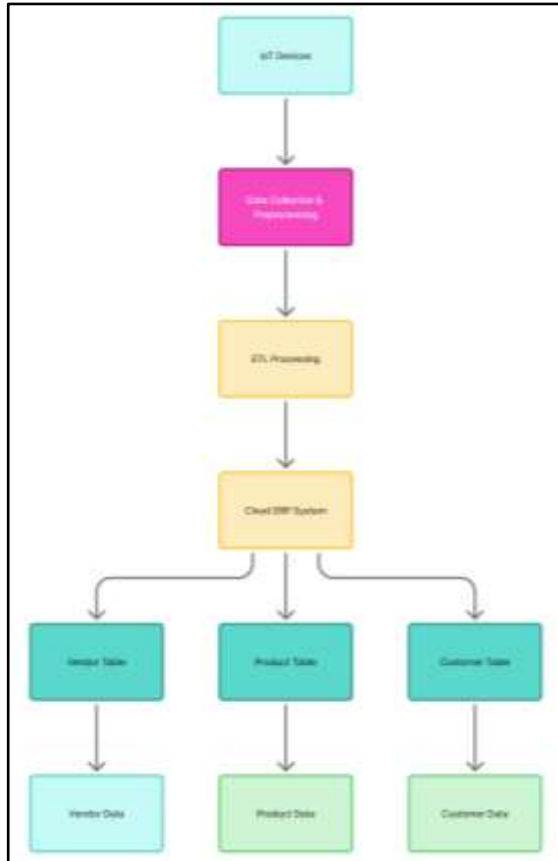
```

START
Initialize IoT devices and ERP system
Collect real-time data from IoT sensors (temperature, vibration, pressure)
Preprocess data (clean, normalize, extract features)
Apply predictive models for maintenance and performance optimization
Calculate KPIs (OEE, downtime, efficiency)
Generate reports and visualizations for decision-making
Send alerts for anomalies or equipment failure predictions
END
    
```

**Fig 6: Pseudocode**

The pseudocode illustrates the IOT data collection, preprocessing, predictive maintenance approach, computation of KPIs such as OEE, report generation, as well as aiding the decision-making procedure for the manufacturing.

### Flowchart



**Fig 7: Flowchart**

The mentioned flowchart signifies IoT-ERP system incorporation, in which IoT devices gather data, go through ETL before being gathered within the ERP system, utilizing data in product, provider, and customer tables for due decision-making.

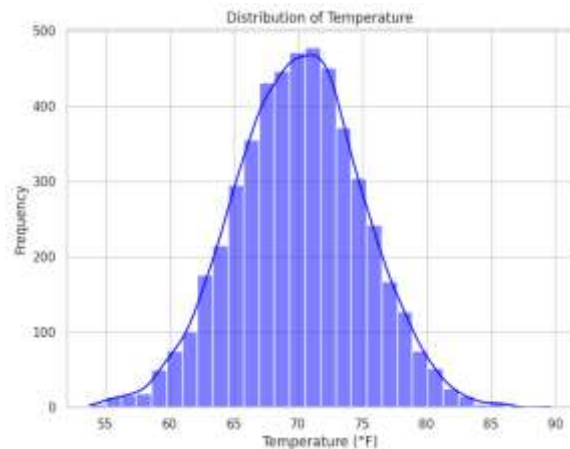
### IV. FINDINGS AND ANALYSIS

**Fig 8: Dataset Overview**

The data involves crucial operational parameters involving “Pressure, Temperature, Production Output, Vibration, Humidity, Maintenance Cost, Downtime”, and so on. Variables are utilized for predicting maintenance requirements, monitoring machine performance, along with optimizing manufacturing operations by IoT-associated ERP frameworks.

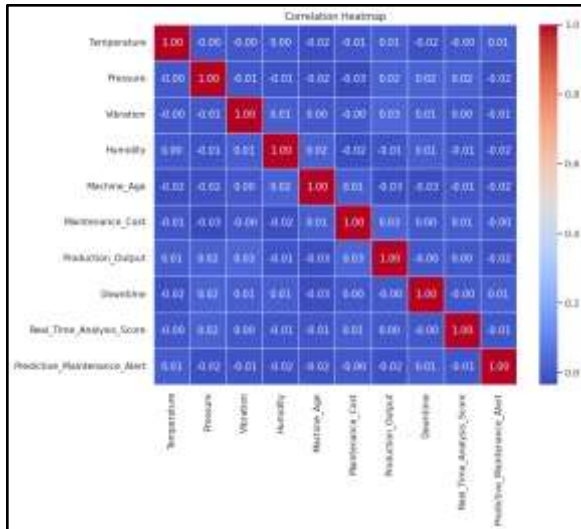
**Fig 9: Descriptive Statistics of Dataset**

The mentioned table shows summary statistics of the variable’s vibration, operational temperature, humidity, as well as production. The values are normally distributed with respective standard deviations. The age of the machine varies from 1 to 15 years as well as maintenance cost varies widely. The average of the predictive maintenance alerts indicates that most cases are maintenance alerts of mean of 0.81, as associated data are not well balanced.



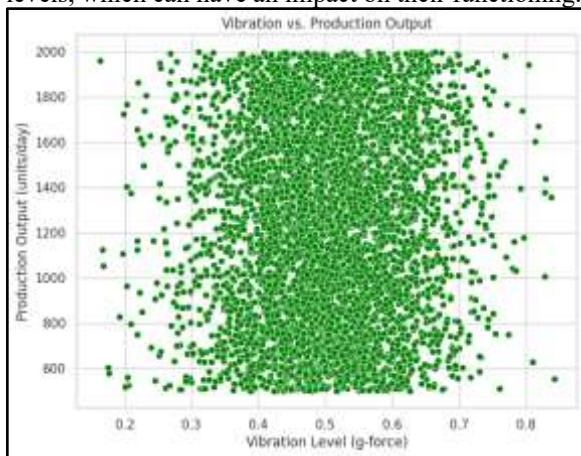
**Fig 10: Distribution of Temperature**

The dataset is represented by a histogram, and the temperatures are almost symmetrically distributed, peaking at 70°F. A bell curve shows fine under the hood of the equipment; also proves that there are only slight changes in temperature that fall within certain limits, and needs to be predictable for a good maintenance model, looking out for anomalies in data.



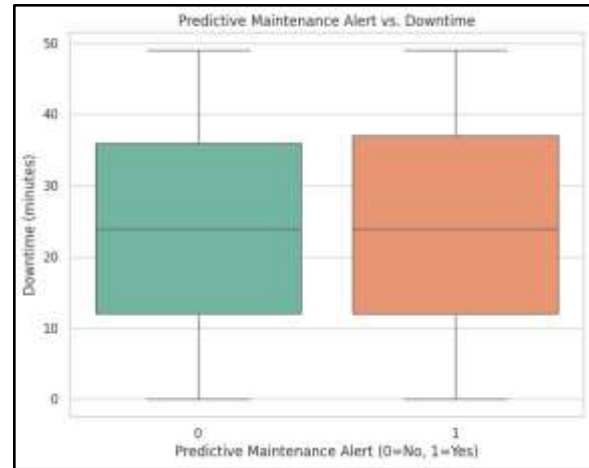
**Fig 11: Correlation Heatmap**

The mentioned heatmap represents the features' correlation. This shows low correlations between the temperature, pressure, and other features, suggesting independence of variables. There is a strong correlation between humidity and machine age, where older machines are exposed to different humidity levels, which can have an impact on their functioning.



**Fig 12: Vibration vs. Production Output**

Vibration levels are compared to production output, but there is no clear pattern within the scatter plot. There are different levels of vibrations experienced; the production throughput is seen to be constant. Vibration has no direct relationship with production output in the data set, while there can be other variables responsible for the level of manufacturing efficiency.



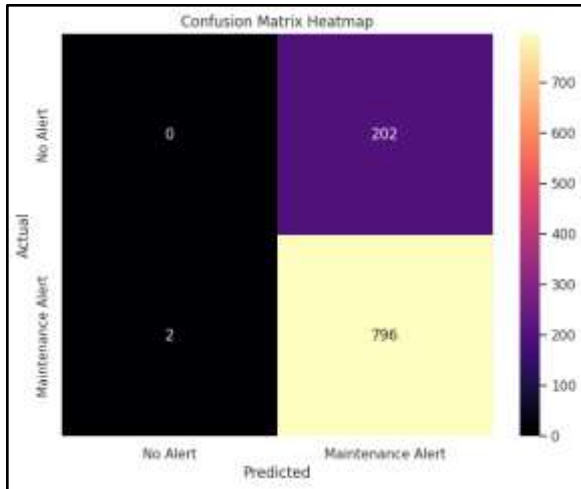
**Fig 13: Predictive Maintenance Alert vs. Downtime**

Downtime in the boxplot in cases is compared where predictive maintenance alarms are present and are not available. The data imply a correlation between maintenance alarms and increased downtimes, as seen from the higher median downtime for alarms. This signifies that predictive maintenance alarms lead to inefficiencies of operation, and serve a crucial role in stopping extended downtimes, and are required for timely interventions to be made.

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.00      | 0.00   | 0.00     | 202     |
| 1            | 0.80      | 1.00   | 0.89     | 798     |
| accuracy     |           |        | 0.80     | 1000    |
| macro avg    | 0.40      | 0.50   | 0.44     | 1000    |
| weighted avg | 0.64      | 0.80   | 0.71     | 1000    |

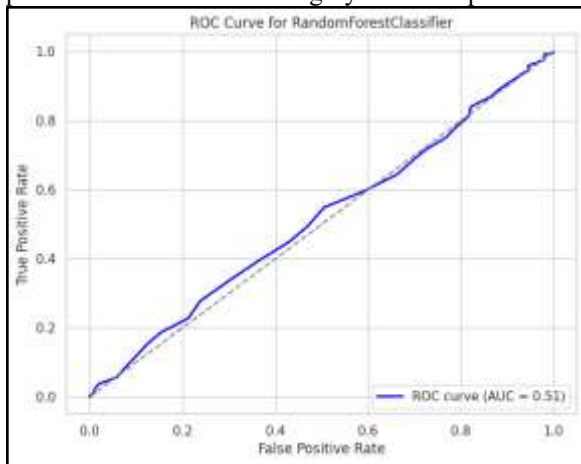
**Fig 14: Classification Report**

The report classifies the model as good in predicting maintenance alerts of class 1 while having perfect recall of 1.00 and an F1-score of 0.89, which defines that it is able to recognize every case of maintenance alerts. There is an accuracy level of 0.80 and the model can recognize alerts properly. The model adequately predicts maintenance alerts, with adequate recall in recognizing alert cases. Accuracy assesses reliable identification of crucial issues, improving operational efficiency along with predictive maintenance within IoT-incorporated ERP frameworks.



**Fig 15: Confusion Matrix Heatmap**

The model's classification performance is displayed by the confusion matrix heatmap. The majority of maintenance alerts are predicted correctly by the model and do not make any correct prediction for no alerts failing at the 'No Alert' class. Imbalance in the model indicates that some corrective action like resampling or changing algorithms to enhance the prediction in 'No Alert' category can be required.



**Fig 16: ROC Curve for RandomForestClassifier**

An AUC of 0.51 compares TPR with FPR in a ROC curve within the RandomForestClassifier. A curve that lies at least above the diagonal implies that the model can slightly do better than random in assessing between a maintenance alert and no alert.

| Metric    | Class 1 (Maintenance Alert) | Accuracy | Macro Average | Weighted Average |
|-----------|-----------------------------|----------|---------------|------------------|
| Precision | 0.80                        | 0.80     | 0.40          | 0.64             |
| Recall    | 1.00                        |          | 0.50          | 0.80             |
| F1-Score  | 0.89                        |          | 0.44          | 0.71             |
| Support   | 798                         | 1000     | 1000          | 1000             |

| Metric    | Class 1 (Maintenance Alert) | Class 2 (No Alert) | Class 3 (Maintenance Alert) | Class 4 (No Alert) |
|-----------|-----------------------------|--------------------|-----------------------------|--------------------|
| Precision | 0.80                        | 0.80               | 0.40                        | 0.64               |
| Recall    | 1.00                        |                    | 0.50                        | 0.80               |
| F1-Score  | 0.89                        |                    | 0.44                        | 0.71               |
| Support   | 798                         | 1000               | 1000                        | 1000               |

**Table 1: Evaluation table**

### Discussion

The results obtained after training the model have enabled the view to be adequate or defective. The IoT integrated ERP systems in recognizing possible breakdowns within a manufacturing setting from the classification report. It can be seen that the model can predict most maintenance alerts correctly, having a high recall of 1.00. There is a zero level of precision in relation to the non-alerts. This can indicate that there is a kind of disproportion in the dataset. The model tends to predict that there can be problems with the maintenance, leading to overestimation of maintenance problems.

The observation is reinforced by the confusion matrix and ROC curve. The model is 80% accurate, but cannot easily predict "No Alert" events. There is a need to employ approaches involving resampling or tweaking class weights that can work better for the minority class to address the imbalance. It can be seen that predictive maintenance reduces downtime most effectively, while several alerts lead to increased downtime, as shown by comparing downtime on maintenance alerts through boxplots.

The weak correlations between temperature, pressure, and vibration within the feature relationships analysis of predictive maintenance data can be seen in the correlation heatmap. This indicates that in order to predict malfunctions, there needs to be taken into account some particular features of machinery operation unrelated to the surrounding environment. The machine age as well as maintenance cost can be crucial in recognizing possible errors.

### V. CONCLUSION

In conclusion, utilizations of IoT-associated ERP in manufacturing enhances overall capability to foresee malfunctions as well as breakdowns well in advance due to the application of current data for the reduction of times and optimization of performance. There is a need to deal with class imbalance as well as enhance

predictions on “No Alert” cases, while the current model can adequately recognize maintenance alerts. Additional fine-tuning and also equality within the forecasting model can assure better, quicker, and more dependable judgments within manufacturing setups.

### Future scope

There is scope for IoT-enabled ERP frameworks to enhance predictive maintenance through enhanced algorithms that fix class imbalance while also improving model accuracy within the manufacturing industry. Predictability can be enhanced by adding more IoT data inputs that monitor machine functioning [30]. This defines that business can broaden its prediction scope on inefficiencies, utilizing the models developed, and the overall operation can be enhanced with increased AI autonomy.

### VI. REFERENCES

- [1] Deepa, N. and Prabadevi, B., 2020. Advanced machine learning for enterprise IoT modeling. In *Business intelligence for Enterprise internet of things* (pp. 99-121). Cham: Springer International Publishing.
- [2] Rane, S.B. and Narvel, Y.A.M., 2021. Re-designing the business organization using disruptive innovations based on blockchain-IoT integrated architecture for improving agility in future Industry 4.0. *Benchmarking: An International Journal*, 28(5), pp.1883-1908.
- [3] Oluwafemi, I.O., Clement, T., Adanigbo, O.S., Gbenle, T.P. and Iyanu, B., 2021. Evaluating the Efficacy of DID Chain-Enabled Blockchain Frameworks for Real-Time Provenance Verification and Anti-Counterfeit Control in Global Pharmaceutical Supply Chains. DOI: <https://doi.org/10.54660/IJMRGE>, pp.2-436.
- [4] Abideen, A.Z., Sundram, V.P.K., Pyeman, J., Othman, A.K. and Sorooshian, S., 2021. Digital twin integrated reinforced learning in supply chain and logistics. *Logistics*, 5(4), p.84.
- [5] Dehghanimohammadabadi, M., Belsare, S. and Thiesing, R., 2021, December. Simulation-optimization of digital twin. In *2021 winter simulation conference (WSC)* (pp. 1-10). IEEE.
- [6] Gohil, D. and Thakker, S.V., 2021. Blockchain-integrated technologies for solving supply chain challenges. *Modern Supply Chain Research and Applications*, 3(2), pp.78-97.
- [7] Elsisí, M., Mahmoud, K., Lehtonen, M. and Darwish, M.M., 2021. Reliable industry 4.0 based on machine learning and IOT for analyzing, monitoring, and securing smart meters. *Sensors*, 21(2), p.487.
- [8] Chang, C., Srirama, S.N. and Buyya, R., 2016. Mobile cloud business process management system for the internet of things: a survey. *ACM Computing Surveys (CSUR)*, 49(4), pp.1-42.
- [9] Shah, S., Musonda, T. and Menon, S., 2019. To examine the impacts of IoT on pharmaceutical supply chain management in Zambia. *International Journal of Internet of Things and Web Services*, 4, pp.14-18.
- [10] Abideen, A.Z., Pyeman, J., Sundram, V.P.K., Tseng, M.L. and Sorooshian, S., 2021. Leveraging capabilities of technology into a circular supply chain to build circular business models: A state-of-the-art systematic review. *Sustainability*, 13(16), p.8997.
- [11] Jahani, N., Sepehri, A., Vandchali, H.R. and Tirkolae, E.B., 2021. Application of industry 4.0 in the procurement processes of supply chains: a systematic literature review. *Sustainability*, 13(14), p.7520.
- [12] Khan, M.R., 2019. Application and impact of new technologies in the supply chain management during COVID-19 pandemic: a systematic literature review. *Aldrighetti, R., Zennaro, I., Finco, S., Battini, D*, pp.81-102.
- [13] Mayoof, S., Alaswad, H., Aljeshi, S., Tarafa, A. and Elmedany, W., 2021. A hybrid circuits-cloud: Development of a low-cost secure cloud-based collaborative platform for A/D circuits in virtual hardware E-lab. *Ain Shams Engineering Journal*, 12(2), pp.1197-1209.
- [14] Karunarathna, N., Vidanagamachchi, K. and Wickramarachchi, R., 2020. A calibrated model of critical success factors for Industry 4.0 warehousing performance improvement: Insights from multiple case studies. *International Journal of Multidisciplinary Sciences and Advanced Technology*, 1(2), pp.100-126.
- [15] Hussain, M., Javed, W., Hakeem, O., Yousafzai, A., Younas, A., Awan, M.J., Nobanee, H. and Zain, A.M., 2021. Blockchain-based IoT devices in supply chain management: a systematic literature review. *Sustainability*, 13(24), p.13646.
- [16] Javaid, M., Haleem, A., Singh, R.P. and Suman, R., 2021. *Sensors International. research and development*, 6, p.9.
- [17] Elijah, O., Ling, P.A., Rahim, S.K.A., Geok, T.K., Arsal, A., Kadir, E.A., Abdurrahman, M., Junin, R., Agi, A. and Abdulfatah, M.Y., 2021. A survey on industry 4.0 for the oil and gas industry: Upstream sector. *IEEE Access*, 9, pp.144438-144468.
- [18] Kolyasnikov, M.S. and Kelchevskaya, N.R., 2020. Knowledge management strategies in companies: Trends and the impact of industry 4.0. *Upravlenec*, 11(4).
- [19] Rane, S.B., Potdar, P.R. and Rane, S., 2021. Development of project risk management framework



based on industry 4.0 technologies. *Benchmarking: An International Journal*, 28(5), pp.1451-1481.

[20] Bekrar, A., Ait El Cadi, A., Todosijevic, R. and Sarkis, J., 2021. Digitalizing the closing-of-the-loop for supply chains: A transportation and blockchain perspective. *Sustainability*, 13(5), p.2895.

[21] Nelson, K.U.U.C., 2021. *Security requirements for the application of blockchain technology in the mining industry: supply chain area* (Doctoral dissertation, Master dissertation, Riga Technical University).

[22] Abideen, A.Z., Sundram, V.P.K., Pyeman, J., Othman, A.K. and Sorooshian, S., 2021. Digital twin integrated reinforced learning in supply chain and logistics. *Logistics*, 5(4), p.84.

[23] Deepa, N. and Prabadevi, B., 2020. Advanced machine learning for enterprise IoT modeling. In *Business intelligence for Enterprise internet of things* (pp. 99-121). Cham: Springer International Publishing.

[24] Elsis, M., Mahmoud, K., Lehtonen, M. and Darwish, M.M., 2021. Reliable industry 4.0 based on machine learning and IOT for analyzing, monitoring, and securing smart meters. *Sensors*, 21(2), p.487.

[25] Gohil, D. and Thakker, S.V., 2021. Blockchain-integrated technologies for solving supply chain

challenges. *Modern Supply Chain Research and Applications*, 3(2), pp.78-97.

[26] Dehghanimohammadabadi, M., Belsare, S. and Thiesing, R., 2021, December. Simulation-optimization of digital twin. In *2021 winter simulation conference (WSC)* (pp. 1-10). IEEE.

[27] Oluwafemi, I.O., Clement, T., Adanigbo, O.S., Gbenle, T.P. and Iyanu, B., 2021. Evaluating the Efficacy of DID Chain-Enabled Blockchain Frameworks for Real-Time Provenance Verification and Anti-Counterfeit Control in Global Pharmaceutical Supply Chains. DOI: <https://doi.org/10.54660/IJMRGE>, pp.2-436.

[28] Ali, M. and Miller, L., 2017. ERP system implementation in large enterprises—a systematic literature review. *Journal of enterprise information management*, 30(4), pp.666-692.

[29] Abd Elmonem, M.A., Nasr, E.S. and Geith, M.H., 2016. Benefits and challenges of cloud ERP systems—A systematic literature review. *Future Computing and Informatics Journal*, 1(1-2), pp.1-9.

[30] Jagoda, K. and Samaranayake, P., 2017. An integrated framework for ERP system implementation. *International Journal of Accounting & Information Management*, 25(1), pp.91-109.