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IIOT: An Infusion of Embedded Systems, TinyML, and Federated Learning in Industrial IoT

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Abstract: With the revolution of Industrial 5.0 the system was modified to smart manufacturing. This Industrial 5.0 is emerging with different technologies such as IoT which provide real-time monitoring, analysis, and data fetching. For the novelty in II0T Application, this article investigates the combination of embedded systems, Tiny Machine Learning (TinyML), and Federated Learning (FL). Data privacy is ensured by Federated Learning (FL), and local data processing becomes efficient through Tiny Machine Learning (TinyML). This infusion promises to decrease latency, increase productivity, and improve data security. As previously unsolvable issues or problems are being addressed with renewed enthusiasm, new paradigms for development and research are needed. The goal of this article is to provide a platform and overcome the knowledge gaps for future revolutionary research projects that will leverage the growing trends of embedded devices influenced by compressed artificial intelligence (AI) models [18]. Moreover, will discuss about the TinyML, federated learning (FL) that permits the models to be trained locally on edge devices by utilizing their data as well as reducing the requirement for centralized data accumulation that may be even impossible in fewer Internet of Things (IoT) situations. It charts the development of embedded devices and wireless communication technologies, demonstrating the advent of Internet of Things applications across a spectrum of industries. In addition, the paper conducts a thorough cutting-edge technology to find recent works that use TinyML models to readily available embedded devices, and talks about recent research trends.

Keywords: Tiny Machine Learning(TinyML); Federated learning(FL); Industrial Internet of Things (IIOT); Support Vector Machine (SVMs); Random Forest (RF); Decision Tree (DT).

1. Introduction

By permitting smart and intelligent operations through automated decision-making, interconnected devices, and advanced data analytics, the Industrial IOT revolutionizes industries and different sectors. The integration of Federated Learning (FL), Tiny Machine Learning (ML), and Embedded Systems significantly enhances this field by providing effective, secure, and scalable solutions. Dedicated computer systems, called embedded systems, are supposed to perform the multiple functions within the larger system. On the other hand, "TinyML" emphasizes the adaptation of resource-constrained devices to make real-time decision-making by using Machine learning (ML) models. Federated Learning (FL) diminishes the need for centralized data storage through the provision of decentralized training data as well as enhances privacy.

The execution of Machine Learning (ML)-driven Internet of Things (IoT) applications generally requires the processing of data by sending the gathered data to central cloud servers as discussed in the research article [1]. Due to application-specific security difficulties, network constraints, and security concerns, this might not be feasible as well. This paper discusses the methodology for on-board training that integrates Federated Learning (FL) and Transfer Learning (TL) as well as for improving the performance of the model; the combination of them is worthwhile in different situations. After being trained on numerous datasets [2], In Federated Learning (FL), many models are "merged" to generate a single model. As a consequence, privacy is protected as data is generated and handled on local devices. Transfer Learning (TL) is used in paired with this approach to increase the efficiency and accuracy. This research analyzes the synergy between these technologies in the Industrial Internet of Things (IIOT) by evaluating the performance of Random Forest (RF) and Support Vector Machine (SVM) models in anomaly detection as well as in predictive maintenance tasks [16]. An Infusion of Embedded Systems, TinyML, and Federated Learning in Industrial IoT has the following research objectives:

- Data is collected from several industrial deployed sensors.
- Data preprocessing includes the cleaning of the dataset by handling and removing missing values, encoding categorical variables, normalizing sensor readings, and segmenting data into testing and training sets.
- based on performance evaluation and predictive maintenance, Random Forest and Support Vector Machine (SVM) are selected.
- Machine Learning (ML) models: Random Forest and Support Vector machine models are used to train the data, including both normal and failure states.
- After training the models, they are put to use on edge devices or continuously monitoring the real-time sensor data.
- By identifying deviations from normal operating conditions, the models forecast when and which part of the equipment is likely to fail.
- When an expected failure is detected, the system generates alerts for maintenance personnel by providing the details on its urgency and predicted.
- The system is continuously enhanced in order to increase the prediction models' accuracy and dependability

The rest of the paper is organized as follows: The literature review is discussed in Section 2, Background in section 3, Section 4 offers the Proposed Methodology and the implementation in Python. The conclusion will be discussed in Section 5.

2. Related Work

With the fusion of Internet of Things (IoT) and Artificial Intelligence (AI) and that has prompted enormous changes in a variety of industries within the last ten years, cloud computing has become an essential agent of innovation.AI applications have demonstrated the remarkable accuracy in such as autonomous cars and anomaly detection despite being resource-intensive[3]. Conventional cloud-centric approaches have been adopted and applied to test the massive amounts of data produced by connected devices, which led to an edge computing revolution. In industrial environments with rigid operating requirements, edge computing enhances contextual cognition and real-time responsiveness by processing the data near its origin. Despite its immense potential, the challenges of coordinating the inconsistent software and hardware systems prevent edge computing from being widely used. Micro service and Infrastructure digitalization are important technologies, and Kubernetes is a platform that helps with lifecycle management and automation. Limited devices with the integration of powerful AI is a revolutionary development, where low-cost single-board computers (SBCs) and microcontroller units (MCUs) are crucial components. Anomaly detection in a wastewater management plant by using an inexpensive IoT kit is discussed in this research article [3], exploring an efficient edge computing system for harsh industrial settings. By establishing a TinyML pipeline, the kit ensures data integrity using Blockchain technology and accomplishes the machine learning workflow on a limited device. By developing an unsupervised, adaptable, and Tiny-MLOps pipeline anomaly detection system designed for challenging industrial environments, this research improves previous work.

By going beyond its initial meaning to refer to a variety of production processes, the term "SMART" is now commonly utilized in the wider context of Industry 4.0. The evolution of this sector is emphasized by terms like smart supply chains, smart and intelligent factories, smart supply chain management, and smart manufacturing. New technologies like Artificial Intelligence (AI), Big Data, and IoT are integrated as part of this process of "smartification", through the creation of smart factories that prioritize data management. For ensuring the quality of the product and maintaining production facilities, anomaly analysis becomes essential in these industries. Analysis of Data is also critical for monitoring, smart design, controlling, planning, and machining. Since conventional anomaly detection techniques, models that distinguish the irregular data from normal data are necessary, such as Bayesian classifiers, support vector machines (SVM), and deep neural networks, which often fail to handle industrial data. This paper [4] describes an approach to filter data at the edge level by reducing the storage costs and telecommunication through concentrating on erroneous data by using research on Edge Intelligence (EI) and its application in analyzing data anomalies by Zhi Zhou et al. [4].

A network of tangible items, including actuators, sensors, microcontrollers (MCUs), and actuators, which are frequently utilized because of their adaptability and affordability, together form the Internet of Things (IoT). At the edge, Machine learning (ML) must be integrated as IoT devices flourish. Unfortunately, when implemented on Microcontrollers (MCUs), classic deep learning models face difficulties, which are resource-constrained and often low-power. Tiny Machine Learning (TinyML) resolves this issue by enabling the Neural Network (NN) functionality on MCUs as well as providing the advantages, which include decreased latency, increased energy efficiency, and enhanced privacy. While on the other hand, some existing frameworks, such as TensorFlow Lite for Microcontrollers and CMSIS-NN, enable NN inference, they are not able to adjust in real-time to new input, which represents significant challenges in dynamic and distributed situations.

The suggested [5] TinyML (TinyML with online learning) architecture enables MCUs to carry out incremental learning directly at the edge by constantly adding new information to the model in order to get around this. The help of this [5] C++ programmed system may enhance the efficiency of pre-trained models and new patterns from data as demonstrated by practical use cases on an Arduino Nano 33 BLE Sense board. MCUs may now benefit from incremental online learning in unique and different patterns by using TinyOL, which enables on-device post-training and dynamic model updating [5].

With the development of smartphones along with other personal gadgets, particularly for indoor navigation technology, Information and communications technology [19] (ICT) has grown significantly. Indoor location systems that make use of protocols and mobile device sensors are outperforming Wi-Fi-based approaches just because of Bluetooth's low power consumption. By delivering information and customized offers, it improves the consumer experience by utilizing applications such as location-based marketing. This paper [6] describes an Internet of Things (IoT) system that predicts the labelled object placements inside interior areas using machine learning (ML). Through scanning stations, data is collected by using a fingerprinting approach, which is possible through a deep learning model that helps to track things properly. This is made possible because of RSSI levels from Bluetooth Low Energy (BLE) signals. The IoT architecture of the system includes Bluetooth Low Energy (BLE), centralized data via MQTT, edge computing-powered storage, and bespoke hardware. While standardized indoor navigation remains a difficult task, using machine learning (ML) approaches such as K-Nearest Neighbor (KNN) and others enhances accuracy by taking challenges and environmental variations into account. That whole hardware-software system [6] demonstrates how ML-based techniques make it possible to achieve accurate indoor navigation in a repeatable and versatile manner.

Table 1. Literature Review Summary

Paper	Field	Year	Sensors	Board	Class
Paper[4]	Industrial	2021	Camera	Jetson Nano	High-end
Paper[5]	Industrial	2021	Vibration	Arduino Nano 33	Low-end
Paper[7]	Industrial	2023	IMUTemperature	ESP32	Low-end
Paper[6]	Industrial	2023	WiFi RSSI	Raspberry Pi Zero	High-end

Problem	Framework	ML Type	ML Models	Deploy
Anomaly detection	-	Supervised	GAN	x
Online learning	TFLM	Unsupervised	DNN	x
Anomaly detection	–	Unsupervised	Isolation Forest	x
Classification	EI	Supervised	DNN	x

3. Materials and Methods:

3.1. Embedded System:

In the Industrial IOT, Embedded systems perform a vital role because they provide the core technology needed for real-time data control, processing, and procurement. Computer units are specially designed for these systems and have great dependability, efficiency, and reliability to carry out specific tasks inside larger industrial and manufacturing environments. In the overall context of the Industrial Internet of Things (IIOT), which enables the monitoring of real-time and automation of industrial operations, embedded systems provide smooth communication among different actuators, controllers, and sensors. Because of their capacity to function in extreme conditions, such as high temperatures, electromagnetic interference, and vibrations, they play an essential role in industrial applications. Moreover, embedded systems are vital to the IIOT's implementation of cutting-edge computing as they provide the decision-making and local data processing that helps to reduce bandwidth and latency. As a whole, the capability to process data locally improves and enhances the dependability and responsiveness of the system by ensuring the uninterrupted and smooth functioning of industrial operations. Embedded systems will continue to be at the leading edge for Industrial Internet of Things (IIOT) development, propelling the improvements in operational effectiveness, predictive maintenance, and automation.

3.2. Edge Computing Vs Federated Learning (FL)

In Industrial IoT [17], Random Forest Regression is a potent machine-learning approach that is used for predictive analyses and decision-making processes. To improve resilience and accuracy, it builds many decision trees during training and averages each one's predictions. In an IIOT environment, the versatility of this ensemble learning technique for handling the massive amounts of diverse data generated from various devices and sensors makes it very useful. For identifying complexity and non-linear correlations in data, Random Forest Regression performs very well, it is useful, especially for predictive maintenance, which uses sensor readings to optimize maintenance plans and forecast equipment breakdowns. To identify the factors that are more effective towards industrial processes, the built-in function Random Forest Regression helps a lot in this case by enabling efficient decision-making. Due to its ability to be robust to outliers, high prediction accuracy, and noisy datasets, it performs efficiently.

Margin Function defined as:

$$mg(x,y) = av_k I(h_k(x) = y) - max_{j \nexists y} av_k \mathrm{I}\,(h_k(x) = j) \quad (1)$$

3.3. Support Vector Machines (SVM) in IIOT:

Support Vector Machines (SVM) plays an important role in IIOT by providing reliable and efficient solutions for a wide range of regression and classification applications. Its capability of handling multidimensional complex data makes it an ideal option for IIOT, where it is supposed to be used for quality control, predictive maintenance, and anomaly detection, as well as characterizing the different sensors data into various operation phases. It performs better where there are low variations in data. SVM can also be implemented on edge devices with the help of its kernel trick and parameters adjustment by ensuring that they function efficiently within the IIOT hardware constraints. To achieve high accuracy in monitoring and decision-making processes, industries may increase operational efficiency, boost production, and decrease downtime.

$$y_i[w.u1 + bias] - 1 > 0, i = 1,2,..n \quad (2)$$

In the classification hyperplane equation can be written $w.u1 + bias = 0$.

3.4. Decision Tree (DT) Model:

In IIOT models, the Decision Tree (DT) plays a crucial role because it provides simple and efficient solutions for regression and classification tasks. To provide insights and access the enormous amount of sensor data, it can be used for a variety of operational needs. They are very simple to develop and flexible due to their easy but effective framework. A decision tree (DT) is effective in identifying the patterns and correlations from the data for problem detection, quality control [20], and predictive maintenance. It can also perform well for categorical and numerical data types. On the other hand, Random Forest approaches like pruning and ensemble have the potential to cause overfitting. They can overcome this overfitting issue and help to improve the resilience and accuracy of the model. In the IIOT context, decision tree models play a major role in decreasing downtime, increasing operational efficiency, and ensuring the dependability of industrial operations.

$$Gain(S,A) = \sum_{V\in} V(A) \frac{|S_v|}{|S|} \; Entorpy\,(S_v) \quad (3)$$

3.5. Elastic Net:

For Industrial Internet of Things (IIOT) applications, a regularization technique that combines the properties of L1 (Lasso) and L2 (Ridge) normalization, Elastic Net, is highly beneficial. Data is often characterized by multicollinearity and high dimensionality. In IIOT environments, that can make the model performance optimization and selection challenging. Elastic Net, in a linear fashion, combines the penalties of Ridge and Lasso. Due to this, the model becomes resilient and capable of managing a high number of linked variables that belong to the typical IIOT datasets. It is usually used to develop dependable predictive models for predictive maintenance and anomaly detection. Due to these specific characteristics, these models improve interpretability as well as increase prediction accuracy. For figuring out the major variables that can directly affect the efficiency and functionality of the equipment, Elastic Net plays a vital role. By using Elastic Net, IIOT systems may make better generalizations on unseen data, which will result in quicker maintenance and more precise prediction actions that can reduce downtime, streamline maintenance schedules, and better overall production in industry environments. The Elastic-Net estimator is defined as follows:

$$\beta(enet) = \left(1 + \frac{\gamma_2}{n}\right)\{arg_{min}||y - X\beta||_2^2 + \gamma_2|||\beta||_2^2 + \gamma_1||\beta||1\} \quad (4)$$

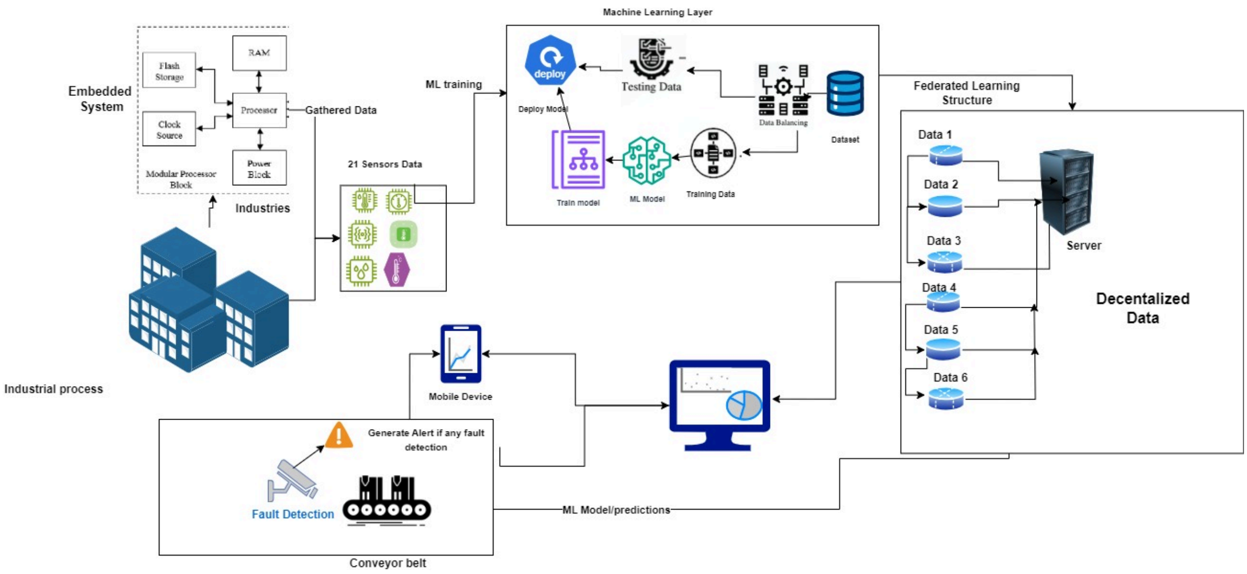


Figure 1. System Overview

4. Proposed Methodology

In IIOT, data is collected from the different sensors, and based on these collected data, equipment failure is predicted, or it is altered before the failure occurs. Due to real-time monitoring, timely maintenance of equipment occurred as well as reducing the downtime.

Based on previous work in IIOT, this article proposed the methodology by combining TinyML models with low-power embedded hardware systems to identify anomalies and to process data in real time at the edge. For ensuring data privacy and confidentiality by using Federated Learning (FL) to train ML models across numerous decentralized devices. For the performance evaluation process, a comparison of different ML models, such as Random Forest, Support Vector Machine (SVMs), Decision Tree (DT), and Elastic Net, are used in various IIOT scenarios. The mentioned working steps are involved. In Figure 2, for applications in sectors like manufacturing, logistics, or smart buildings, this methodical methodology efficiently leverages sensor data to support continual model upgrades and real-time decision-making.

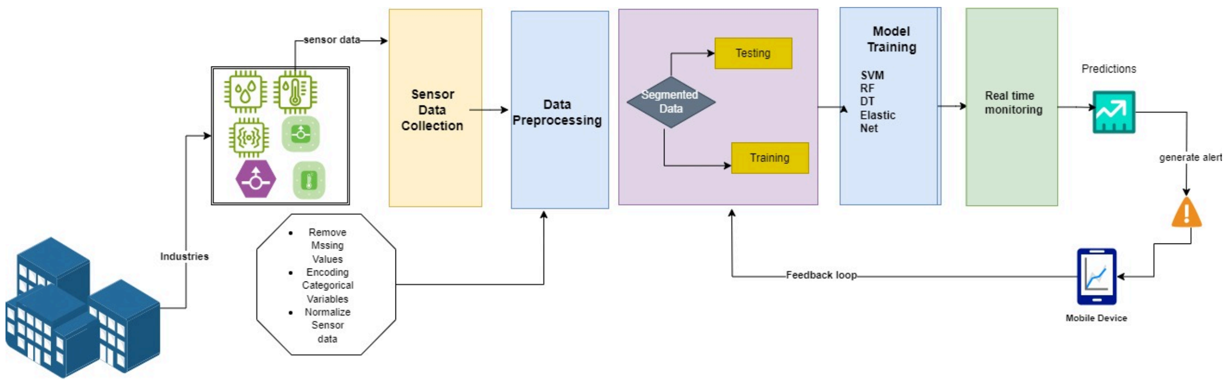


Figure 2. Block Diagram

4.1. Data Collection:

In IIOT, data is collected from several industrial deployed sensors. The dataset contains collected metrics, including vibration, temperature, pressure, and operating status.

4.2. Data Preprocessing:

Data preprocessing includes the cleaning of the dataset by handling and removing missing values, encoding categorical variables, normalizing sensor readings, and segmenting data into testing and training sets.

4.3. Model Selection:

Based on performance evaluation and predictive maintenance, Support Vector Machine (SVMs), Random Forest models, Decision Tree (DT), and Elastic Net are selected because of their robustness and widespread use for classification and regression tasks.

4.4. Model Training:

Machine Learning (ML) models are used to train the data, including both normal and failure states. These models learn correlations and patterns between sensor readings and equipment failures.

4.5. Real-Time Monitoring:

After training the models, they are put to use on edge devices or continuously monitoring the real-time sensor data. These models examine the incoming data to detect anomalies or malfunctions that suggest potential failures.

4.6. Anomaly Detection and Prediction:

By identifying deviations from normal operating conditions, the models forecast when and which part of the equipment is likely to fail. Based on patterns learned during the training phase, this prediction has been made.

4.7. Alert and Maintenance Scheduling:

When an expected failure is detected, the system generates alerts for maintenance personnel by providing the details on its urgency and predicted outcome. This makes it possible to schedule preventive maintenance, which ensures that the machinery is maintained before a breakdown happens.

4.8. Feedback Loop:

The system is continuously enhanced to increase the prediction models' accuracy and dependability through the input of maintenance results and activities.

5 . Simulation and Results:

5.1. Implementation in Python:

Relationship between various features (sensor readings and operational settings) and a target variable, specifically Remaining Useful Life.

As you can see, Figure 3 shows the relationship for data analysis, including Sensor reading, operational setting, target variable, and especially remaining useful life. This shows random variance and high resolution of the different sensors. After removing the outliers, we achieved a more interesting and informative graph.

As you can see, Figure 4 shows the relationship between data analysis, including operations and sensors [13]. This shows the random variance and high resolution of various sensors. After removing the emissions, we reached a more interesting and informative plotting.

There are raw data plotted as sensors. It includes all the sensors. Figure 5 shows a histogram index of the feature and Importance, based on all the results the difference values Like Accuracy determined.

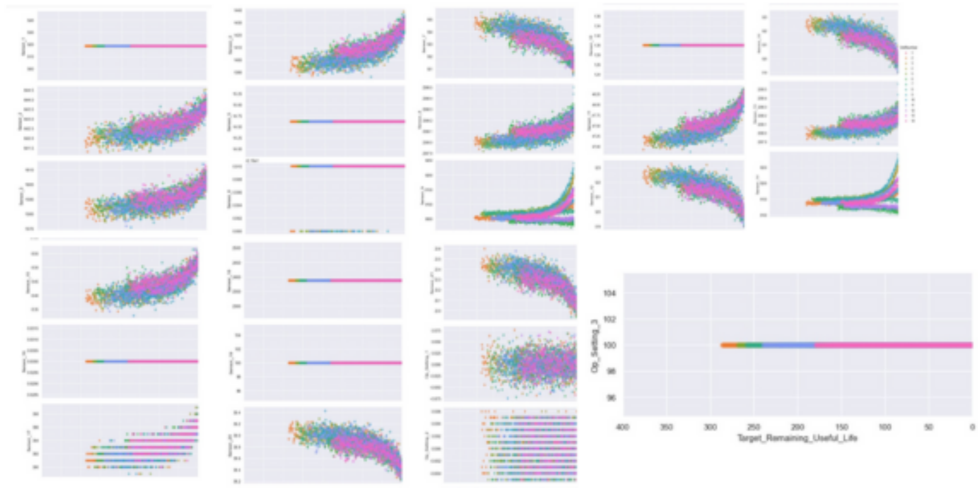


Figure 3. Relationship between Various Features

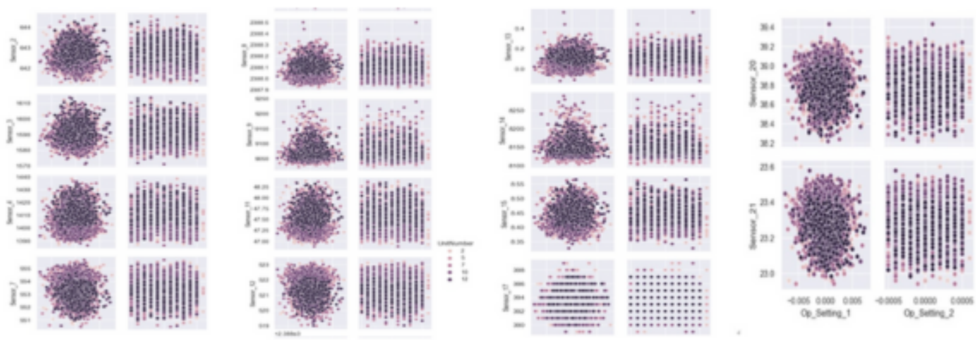


Figure 4. Relationship Between Operational and Sensor

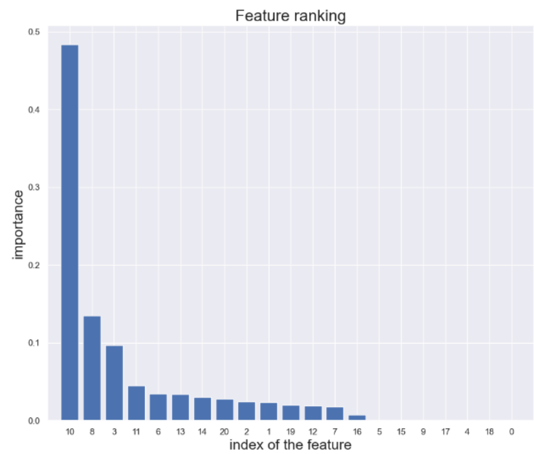
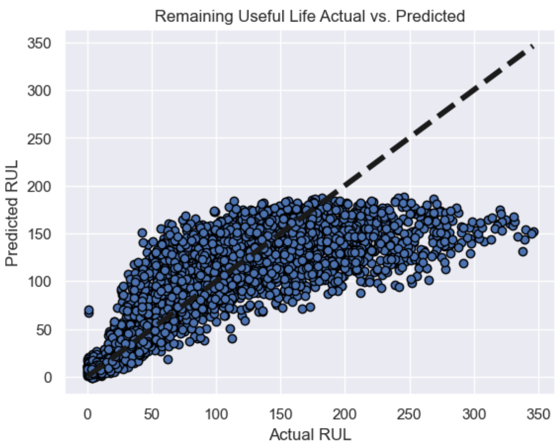


Figure 5. Feature Ranking

Table 2. Compare the Performance of all Models

Model	Mean Squared Error	Mean Squared Error	Mean Absolute Error	R-Squared
Random Forest	1779.135176	1779.135176	30.019037	0.623557
Elastic Net	2043.031134	2043.031134	34.600517	0.567720
Support Vector Machine	1860.482775	1860.482775	30.283873	0.606345
Decision Tree	1940.180394	1940.180394	31.797718	0.589482

Table 2 illustrates the performance of SVM with MAE (30.238873) and MSE (1860.482775), respectively. Although it is not as strong as Random Forest, the R-squared score of 0.606343 indicates a good explanation of variability. The Random Forest model, which is distinguished by its low error rates and greater capacity to explain variance in the dependent variable, outperforms the other four models assessed according to the criteria given.



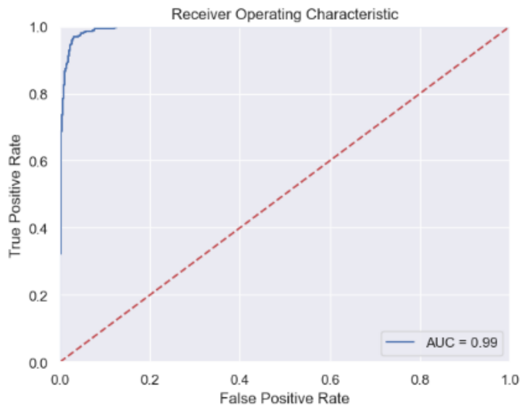


Figure 6. Actual Vs Predicted Useful Life **Figure 7.** Receiver-operating characteristic curve

Random Forest Regression (RFR) and Gradient Boosting Regression (GBR) are essential for forecasting RUL in the given system. On the contrary, GBR uses the series. Subsequent decisions are improved periodically. It fixes prediction accuracy and its predecessor errors. Both methods increase the overall predictive model Validity by using input information Operation status. Figure 6 shows the actual rule with the forecast [14]. Figure 7 shows the performance of the binary classifier on data displayed on a single graph receiver operating characteristics for comparison of the ROC curves obtained by using the machine learning classifier [15] X represents the false positive rate, and Y represents the True positive rate.

6. Conclusion:

In conclusion, a strong foundation for improving predictive maintenance and anomaly detection in IIOT systems is presented by the fusion of federated learning (FL), TinyML, Embedded Systems, and sophisticated ML models such as Random Forest (RF) models, Support Vector Machine (SVMs), Decision Tree (DT) and Elastic Net. Based on the measured result and their performance measurement, we prefer to use the Random Forest Regression Model. This approach uses decentralized training to ensure data privacy and confidentiality, simultaneously dealing with the limitations of embedded devices with low resources. Local data processing at the edge helps in reducing latency and bandwidth consumption, leading to more effective and responsive industrial processes. Through the utilization of these methodologies, industries may get better random forest accuracy 97.9 % in tracking the condition of their equipment, schedule maintenance proactively, and ultimately save operational costs and downtime.

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