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IOT – Integrated Adaptive Edge Intelligence for Predictive Diagnostics In Smart Industrial Environments

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Abstract
The operation of machines continuously is essential in productivity, and breakdowns lead to downtimes, repairs and utilities. This paper provides a predictive diagnostic system based on Adaptive Edge Intelligence in industries. On the edge devices, real-time sensor data is preprocessed, features extracted and anomalies identified and this minimizes the latency and reliability. Patterns are updated by adaptive learning according to changes in situations. ThingSpeak cloud facilitates monitoring and visualization, warning generation, better prediction accuracy, response time, safety, productivity, and less downtime.

Keywords: *Embedded Systems, IoT devices, Real-Time Monitoring, Sensor Data Acquisition, STM32, Machine Learning.*

1. Introduction

Industry 4.0 In the framework of the Industry 4.0 paradigm the industrial sector is quickly moving into the direction of automation and digital transformation. As a student, one can easily understand how important the constant and stable operation of machines is to retain productivity, quality of products, and competitiveness. Even short opera interval can accumulate serious financial damages, disrupt working processes, increase maintenance activities and drain operational productivity. The conventional condition-monitoring is largely concerning the periodic manual inspections and analysis in clouds, which tends to lack the timing, as well as, actionable knowledge that we usually require. The communication lag, dependency on the constant internet connection and inability to change the behavior of machines flexibly do not fit the contemporary shop floor. Predictive diagnostics is emerging as the choice solution since it narrows down to the possible failures until the actual failures occur. Nevertheless, most of the solutions that exist today are excessively attached to the cloud computing and introduce latency and data overload and slow responses when events take place on-the-fly. That is why edge computing has intervened as a viable solution: it allows us to perform intelligent data processing in the location of the equipment. Through sensor data analysis at the sensor level we reduced communication bloat, accelerated response times and made faster decisions at a machine level. The proposed paper presents an Adaptive Edge Intelligence system of Predictive Diagnostics in Intelligent Industrial Environment. The system continues to capture live sensor data on the machines including temperature, vibration, pressure, motor speeds etc. A local preprocessing, noise filtering, feature extraction and anomaly detection, is then performed on an embedded edge device and ensures the diagnostics remain available even when the network is out of service. This edge level crunching significantly reduces the latency whilst maintaining the data reliable. The processed diagnostics are pushed to the ThingSpeak IoT cloud platform in order to increase remote accessibility and visualization. ThingSpeak allows us to visualize real-time graphs of machine parameters, thus, allowing us to observe operational patterns and unusual patterns through time- series charts. Such visual indications assist maintenance experts to identify the initial signs of problems and to have an idea of how a machine works

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without being present at the site. Besides, the long-term storage of ThingSpeak allows us to sift through the past, which is essential in refining the predictive capability. The system is baked with an adaptive learning mechanism to ensure continuous adjustments in diagnostic models as the environment and the conditions of the different machines change. This shuns the manual changes or complete retraining which the needle often undergoes. With the addition of the adaptive edge intelligence and machine learning and ThingSpeak-based visualization of IoT, the system eliminates the early fault detection, timely alerts and smart maintenance planning. The reward is that downtime of machines is reduced, safety measures are improved, and the efficiency of the entire industry is strengthened to a good extent, contributing to the creation of a stable and future-proof industrial ecosystem.

2. Methodology

2.1.First Module

Data Acquisition and Edge Processing Module This module performs real-time sensing and local processing of machine parameters using an STM32 microcontroller[1], DHT11 temperature-humidity sensor, IR-based motor speed sensor, motor driver, DC motor, I2C LCD, and an IoT communication interface. Sensors continuously measure temperature, humidity, and motor speed during machine operation. The collected sensor[2] data is transmitted to the STM32 where preprocessing such as noise filtering, signal smoothing, normalization, and formatting is performed to ensure data accuracy and consistency[3].

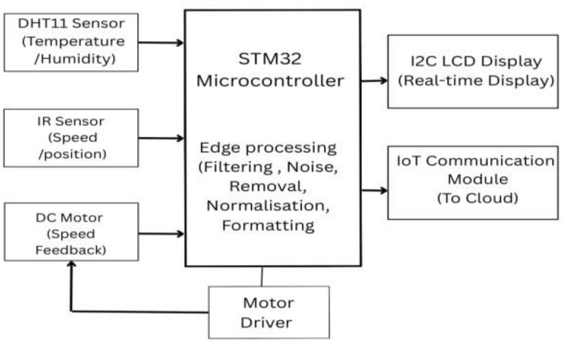

Figure 1 First Module

The motor speed is calculated from IR pulse counts using:

$$RPM=60\times N/t$$

To remove noise and stabilize sensor signals, a moving average filter is applied:

$$y[n]=M1i=0\sum M-1x[n-i]$$

The processed values are displayed on the I2C LCD for real-time hardware verification. After preprocessing, structured data is transmitted through the IoT module to the ThingSpeak platform. Time-series graphs visualize machine behaviour and help identify abnormal trends, ensuring efficient data collection, fast edge processing, and seamless cloud integration[4].

2.2.Second Module

Cloud Analytic and Predictive Intelligence Module (with Formulas) This module focuses on predictive diagnostics and cloud-based analytics using the ThingSpeak platform. Sensor data received from the edge device is stored and synchronized in the cloud for further analysis. Python-based machine learning frameworks process historical and real-time datasets. Feature extraction is performed using statistical and frequency-domain techniques such as mean, RMS, standard deviation, peak value, and Fast Fourier Transform (FFT).These features are used to train models like Random Forest, Support Vector Machine (SVM), and neural networks for machine health prediction[5].

Root Mean Square (RMS):

Used to measure signal energy and detect abnormalities in vibration or sensor data.

$RMS = \sqrt{((1/N) \sum(i=1 \text{ to } N) xi^2)}$

2.3. Fast Fourier Transform (FFT):

$$X(k)=n=0\sum N-1x(n)e-j2\pi kn/N$$

Converts time-domain signals into frequency-domain for identifying hidden fault patterns. The trained models analyze incoming sensor data in real time and classify machine conditions as normal or faulty. Results are correlated with ThingSpeak visual graphs to identify abnormal trends. When faults are detected,

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alerts are generated for timely maintenance. Continuous learning enhances prediction accuracy, system intelligence, reliability, reduces downtime, and improves industrial efficiency shows Figure 2 Second module[6].

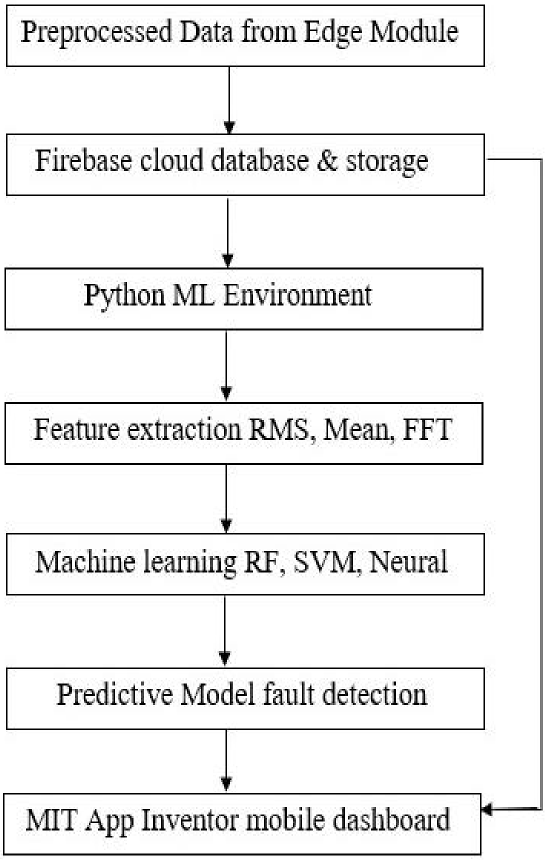

Figure 2 **Second module**

3. System Architecture

The proposed system structure is designed in a layered format to ensure efficient data acquisition, processing, cloud integration, visualization, and decision-making for real-time monitoring and predictive diagnostics of industrial machines. Real-time data is collected using sensors such as the DHT11 for temperature and humidity, and an IR-based motor speed sensor for RPM measurement, which helps identify variations related to machine reliability and operational safety[7]. These sensing elements continuously capture environmental and mechanical parameters, forming the foundational input for further analysis and system intelligence.

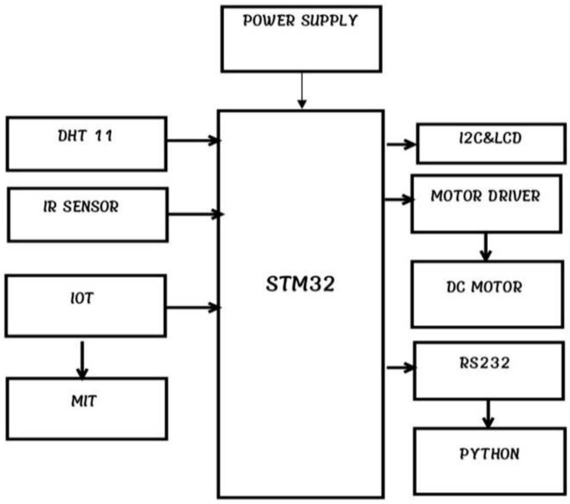

Figure 3 **Block diagram**

The STM32 microcontroller processes the raw sensor signals through noise filtering, smoothing, and normalization, while also performing control functions and displaying values on an I2C LCD for on-site verification. This embedded processing ensures that the acquired data is conditioned, structured, and reliable before transmission. Preprocessed data is transmitted wirelessly via Wi-Fi to the ThingSpeak cloud platform, enabling seamless real-time synchronization and remote monitoring without dependency on wired communication systems. In the cloud, data is stored as time-stamped records and visualized as graphs to analyze trends and detect abnormalities in machine operation over time. Machine learning[8] techniques using statistical and frequency-domain features such as mean, RMS, standard deviation, peak, and FFT are applied to classify machine conditions into normal, warning, or faulty states. A mobile interface developed using MIT App Inventor provides real-time visualization, alerts, and remote monitoring, thereby improving decision-making, enhancing system reliability, ensuring operational safety, and enabling efficient predictive maintenance in modern industrial environments[9].

4. Flowchart

The flowchart represents a predictive maintenance system for industrial machines. It begins with data

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acquisition using DHT11 and IR sensors to measure temperature, humidity, and motor speed. The collected data is processed by the STM32 microcontroller, where signal conditioning and display on an LCD occur. The processed data is then transmitted wirelessly to the cloud for storage and management. Machine learning algorithms analyze the data for classification[10].

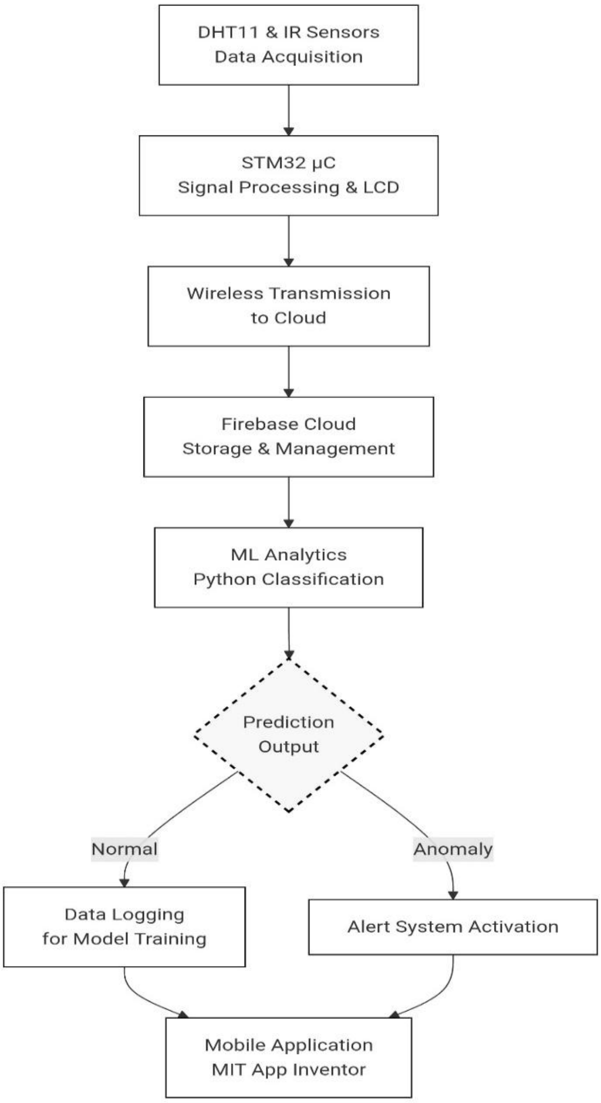

Figure 4 Flowchart

Based on prediction output, if the condition is normal, data is logged for model training. If an anomaly is detected, an alert system is activated. Finally, all results are monitored through a mobile application interface.

Table 1 Existing System Vs Proposed System

Existing System	Proposed System
Maintenance is performed planned during machine failure or continuous during fixed periodic machine inspections.	Maintenance is based on monitoring of operating conditions.
Higher cost due to cost unexpected failure and frequent manual servicing.	Lower operational due to early fault identification and scheduled maintenance.
Machine condition can be checked only through on be site inspection.	Machine parameters accessed easily through connected monitoring units.
Fault identification is structure time consuming and fault depends on skilled personnel.	Simplified allowing faster identification with minimal human effort.
Relies mainly on manual observation and operator for experience.	Uses structured parameters analysis reliable condition assessment.

5. Hardware Requirements

The hardware components will be the basis of the proposed predictive diagnostic system since they will allow us to acquire data in the most accurate way through the most secure means and integrate with the cloud environment to enable us to monitor our data in real-time on the ThingSpeak platform[11].

5.1. Power Supply

All system components such as sensors, the microcontroller and peripheral devices are provided with a stable and regulated power supply. Industrial Varying voltages can cause sensor readings to be inaccurate or microcontrollers to unexpectedly reset. Regulated DC power supply allows the stable operation of the system in a continuous manner and, therefore, makes sensor data consistent that can be subsequently illustrated as stable time-series charts on ThingSpeak[12].

5.2. Microcontroller

The microcontroller of the predictive maintenance system is the STM32. It gathers information using a various number of sensors and initial preprocesses it and takes care of communication with cloud systems to monitor in real time. Its ARM Cortex architecture is high-speed and is able to efficiently implement embedded algorithms, such as feature extraction and edge-level filtering. The STM32 is optimized to fulfill the requirements of industrial IoT applications with low power usage, short response time and various communication protocols to stream data to ThingSpeak to visualize it in a graphical format.

5.3. IoT Module

The IoT module supports wireless communication between the embedded hardware and the cloud infrastructure. It is used to relay real-time sensor data to cloud services to enable monitoring of health parameters of machines remotely. The module provides live updates of the data and the efficient synchronization of sensor data with ThingSpeak dashboards by means of constant connectivity, where sensor data are represented in graphs. Scalability is also improved with the module that enables the connection of a variety of devices over industrial configuration.

5.4. DHT11 Sensor

DHT11 sensor measures both temperature and humidity that are essential environmental conditions that influence the performance of machinery. The abrupt change in these parameters can be a sign of overheating or other unfavorable conditions of operation. The sensor offers a good digital signal and can be tracked to the STM32 microcontroller. The recorded environmental data is sent to the cloud and presented in form of ThingSpeak graphs, which allow tracking the trends and preventing possible abnormal thermal behavior.

5.5. IR Sensor

A speed sensor based on IR is used to measure speed of rotation of the DC motor by sensing infrared reflections or interruption. The changes in the speed of a motor are directly connected to mechanical problems like changes in load, imbalance, or component wear. The IR sensor has a fast response and stable performance hence can be used in diagnostic purposes. The RPM results of this sensor are constantly displayed on ThingSpeak graphs, which constructs the visual analysis of motor behavior with time.

5.6. Motor Driver

The motor driver connects the STM32 microcontroller to the DC motor, which makes it possible to control a motor safely and efficiently. Microcontrollers are not able to provide high current levels, thus the motor driver increases the control signals to control the speed, direction, and torque of the motor. Consistent sensor information is necessary to make the ThingSpeak-based visualization and diagnostic analysis more reliable, which can only be ensured by stable motor operation by the driver.

5.7. DC Motor

The DC motor is an industrial equipment in the system. It also creates realistic conditions of operation, including rotation, changes in speed, and mechanical stress, and enables sensors to record useful information to enable predictive diagnostics. The behavior of motor will give a useful input to machine learning models and will be reported via continuous trends in graphs in ThingSpeak platform, which assists in confirming the performance of the system.

5.8. I2C LCD

Display The I2C LCD display offers on-site display of real-time sensor readings and system state with a minimal amount of wiring. Parameters like the temperature, the speed and system alerts are also shown on the hardware directly which comes in handy during testing and debugging. This local interface is complemented by the remote ThingSpeak graphical visualization in that it allows real-time on-site monitoring without any extra software applications.

6. Software Requirements

The proposed system is based on the software tools that provide the support of embedded programming, cloud communication, data visualization, and predictive diagnostics based on machine learning. The combination of these tools allows to monitor and analyze the machine parameters in real time and graphically with the help of the ThingSpeak platform.

6.1. Arduino Ide

The embedded programs are written, compiled and uploaded using Arduino IDE to the STM32

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microcontroller. It offers a convenient development environment that comes with a large library support to make it easy to interface the sensors, display units, and IoT communication modules. Serial Monitor is inbuilt which will help with debugging and instant testing of sensor outputs during system development and testing. At this point, the processed sensor information relayed by the STM32 is checked before it is uploaded to the cloud hence providing stable data transmission to the graphical visualization of ThingSpeak. Arduino IDE is flexible and easy to use and hence it is best suited to prototyping and industrial monitoring based on IoT in academics as well.

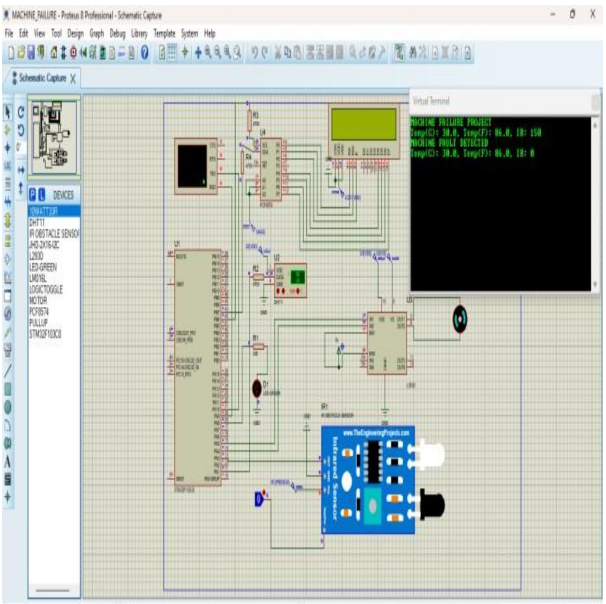

Figure 5 **Arduino IDE**

6.2. Embedded C Language

The control of the STM32 microcontroller is done via embedded C as the main program language. It permits accurate and effective management of hardware parts like sensors, motor drivers and communication interfaces. Embedded C offers low level access to hardware resources which allows control logic and edge level preprocessing activities to run quickly. It is critical because of real-time data acquisition and preprocessing through its efficiency and deterministic nature to ensure the generation of reliable and stable sensor readings to be plotted continuously on ThingSpeak graphs.

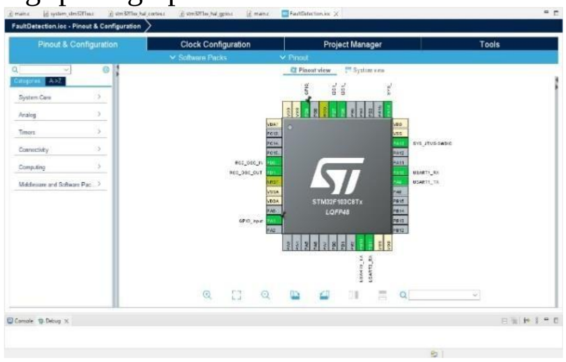

Figure 6 **Embedded C language**

6.3.Python

Cloud level data analysis and predictive diagnostics based on machine learning requires Python.Sensor data stored in the cloud database is accessed with the help of Python-based libraries and processed with the help of historical sensor data. It starts with the cleaning of the data using the noise and outliers, which is then normalized and scaled. The processed data is divided into suitable time windows to analyze them in time. There is extraction of features done both through time- domain and frequency-domain.

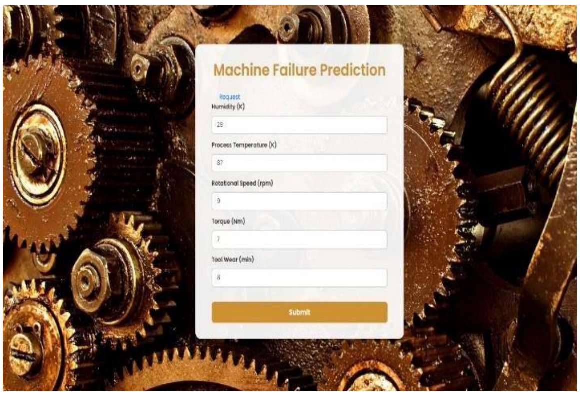

Figure 7 **Python ML**

Mean, RMS, Standard deviation, and peak values are all computed as statistical features whereas frequency-domain characteristics are determined with Fast Fourier Transform (FFT). These characteristics are employed to train and test machine learning models in machine health prediction. The results of predictions are also correlated with ThingSpeak graphical trends, which allow visualizing machine behavior and contributing to

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correct fault identification.

7. Mit App Interface

The MIT App Inventor interface presents a clean machine monitoring dashboard. It displays key parameters such as temperature, humidity, RPM, and machine status in a structured layout. Each parameter is clearly labeled with icons and corresponding values, enabling users to understand real-time conditions easily. The status field indicates whether the system is operating normally or has encountered a failure. A "Back" button is provided for simple navigation. Overall, the interface emphasizes clarity, ease of use, and real-time data display, allowing users to monitor machine performance effectively and quickly identify any issues without confusion.

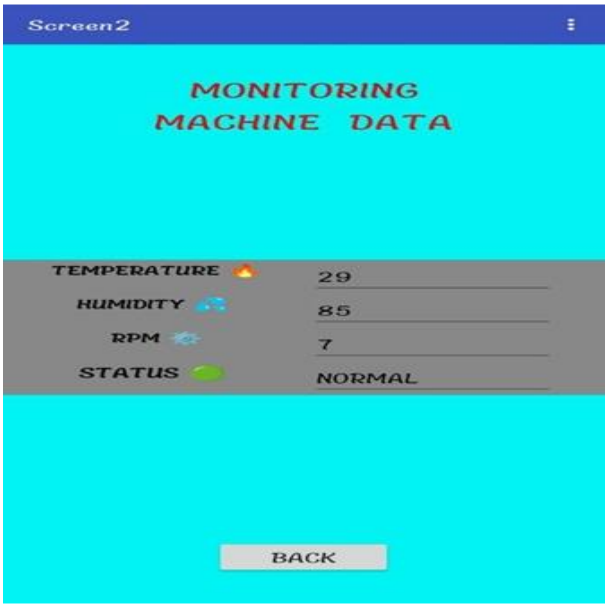

Figure 8 Normal condition

Figure 9 Fault condition

8. Thingspeak Data Visualization

The graphs show machine performance based on temperature, humidity, and motor speed over time. Variations in these parameters indicate the operating condition of the machine. Stable trends represent normal functioning, while sudden increases or irregular patterns suggest faults. Rising temperature, high humidity, or fluctuating speed can signal potential failure. These graphical patterns help in early fault detection, allowing timely maintenance and improving system reliability while reducing unexpected breakdowns and operational downtime.

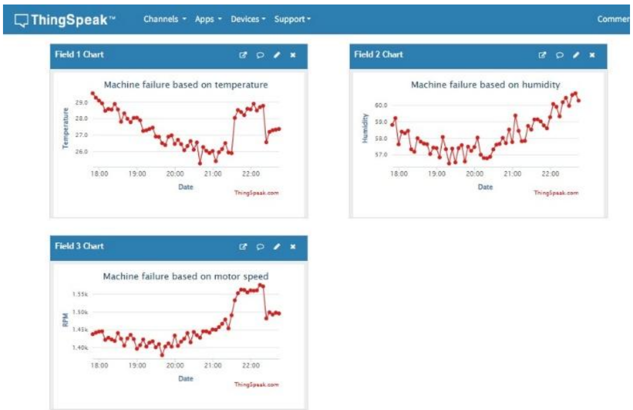

FIGURE 10 Thinkspeak Graph

9. Results And Discussion

9.1. Results

The experimental results demonstrate that the proposed system effectively performs real-time machine monitoring and fault detection by continuously collecting temperature, humidity, and motor speed data using DHT11 and IR sensors interfaced with the STM32 microcontroller. The incorporation of edge-level preprocessing improves signal stability and enhances data accuracy before transmission. The processed data is uploaded to the ThingSpeak platform, where time-series graphs enable clear visualization of machine conditions and operational trends. These graphical representations help in distinguishing between normal and abnormal states. Machine learning models implemented in Python accurately classify machine conditions using both statistical and FFT-based features, achieving high prediction accuracy. During testing, the system

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successfully identified faulty conditions based on speed variations and environmental changes, while real-time alerts were generated whenever abnormal patterns were observed. The system also supports continuous data logging, improving model training and reliability. Overall, the results confirm that the proposed approach is efficient, reliable, scalable, and capable of enabling early fault detection, reducing downtime, and supporting predictive maintenance in industrial environments.

9.2.Discussion

The experimental results demonstrate that the proposed system effectively enables real-time monitoring and predictive diagnostics of industrial machines. Continuous data acquisition of temperature, humidity, and motor speed, combined with edge-level preprocessing using STM32, improves signal accuracy and reliability.The ThingSpeak platform provides efficient data storage and visualization through time-series graphs, allowing clear identification of trends and anomalies. Machine learning models using statistical and FFT-based features achieve high accuracy in classifying machine conditions. The system successfully detects abnormal patterns and generates real-time alerts, supporting early fault identification, reducing downtime, and enhancing decision-making and overall system performance.

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The reference highlight research on IoT, machine learning, edge intelligence, and federated learning for predictive maintenance, enabling real time fault detection, improved efficiency, and reliability.

Journal reference style

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