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IOT Integrated Transformer Health Monitoring and Predictive Maintenance System

Dr.M.T.Hasan[1], Sanjana Surwade[2], Rushikesh Avinash Sarad[3], Ishika Vijay Taklikar[4], Reesha Ali[5], Vedant Lonare[6]
[1]Associate Professor, [2, 3, 4, 5, 6]Research Scholars, Department of Artificial Intelligence and Data Science Anjuman College of Engineering and Technology, Nagpur, Maharashtra, India

Abstract: Power distribution networks depend heavily on transformers, and their failure can seriously interrupt operations. In order to track transformer health and forecast maintenance requirements, this study presents a smart system that integrates IoT technologies. It makes defect detection and condition assessment possible in real time. The system uses a variety of sensors to track important metrics like voltage, current, power, energy, frequency, power factor, and temperature. Data is sent wirelessly through an ESP8266 to the ThingSpeak cloud, where it's analyzed for any irregularities. A machine learning model, trained on historical sensor data, helps predict potential faults by using set thresholds, which aids in early detection and preventive maintenance. To make it even better, the system features a user-friendly dashboard built with Streamlit that offers real-time monitoring, fault classification, and instant alerts. It also explores different communication technologies like GSM, LoRa, Zigbee, and Bluetooth to ensure reliable data transmission. The Random Forest model achieves an impressive 99.2% classification accuracy, demonstrating the system's remarkable fault prediction accuracy. This method reduces maintenance costs, increases transformer dependability, and helps avoid power outages by combining IoT, cloud computing, and AI analytics. In the future, three-phase industrial transformers may benefit from improved scalability and faster fault detection with the integration of edge computing.

I. INTRODUCTION

Transformers are the foundation of power grids because they control voltage throughout transmission and distribution networks, ensuring that electricity flows effectively. They are susceptible to deterioration with time, nevertheless, much like any other vital infrastructure. 70–80% of transformer failures are caused by internal problems such mechanical stress, insulation failure, and overheating. These problems frequently result in unanticipated failures, costly repairs, and extensive power outages. [1]

Periodic inspections—looking for problems at predetermined intervals—have always been the mainstay of transformer maintenance. Despite being the standard for many years, this approach is unable to identify concerns in real time and frequently only identifies problems after they have progressed. This is where contemporary technology comes into play. [2]

Transformer Health Monitoring Systems (THMS) and Predictive Maintenance use IoT sensors and AI-driven analytics to make transformer maintenance more intelligent and dependable. By continuously monitoring vital factors like temperature, voltage, and current, these systems enable early fault identification before problems become serious. This method is revolutionary for power grid dependability because it combines machine learning and IoT-based monitoring to improve safety, decrease downtime, and prolong transformer lifespan. [3]

A. Why Prototyping?

Full-scale transformer monitoring system design is expensive and complicated, needing considerable infrastructure and access to high-voltage power networks. In order to address this issue, we have created a proof of concept, or scaled-down prototype, that incorporates AI-driven fault detection and IoT-based monitoring while simulating actual transformer settings.

This prototype is more than simply a simplified model; it shows how an interactive user interface (UI), machine learning, and sensor data can all be combined to enable proactive, effective transformer maintenance. This prototype opens the door for testing and validation prior to widespread industrial implementation by providing a safe and affordable substitute.

B. Phase-Level Monitoring

The prototype is highly suited for industrial applications since, despite operating at a single-phase level, its methodology is completely scalable to monitor three-phase transformers. Using machine learning algorithms that evaluate real-time sensor data to predict problems before they arise, the system is intended to:

- Detect phase-specific anomalies like overload, underload, and temperature fluctuations, which are early indicators of possible transformer failure.
- Assure scalability so that the system may be expanded to accommodate increasingly intricate power grid transformer layouts.

This prototype provides a scalable and affordable transformer health monitoring system by fusing real-time analytics, machine learning, and IoT-driven monitoring. Such intelligent monitoring systems will be essential to maintaining the energy sector's sustainability, dependability, and efficiency as power networks get more intricate.

II. LITERATURE REVIEW

Since IoT-based transformer health monitoring systems provide automated fault detection, remote monitoring, and real-time data collecting, their integration has drawn a lot of interest. Numerous strategies have been investigated, utilizing wireless communication technologies, sensor networks, microcontrollers, and cloud-based platforms. But even with these developments, problems like communication dependability, scalability, and predictive maintenance still exist.

Breakdown Voltage (BDV) testing was the main topic of a recent study by Jasper et al. (2023) that presented an IoT-enabled smart condition monitoring tool made especially for oil-filled transformers. The method reduces human error and increases the effectiveness of remote monitoring by automating BDV readings through the use of solenoid valves and pumps[4].This technique evaluates oil degradation, a crucial component of transformer longevity, in contrast to conventional methods that depend on temperature and current sensors. Although this approach greatly improves monitoring accuracy, it is not appropriate for large-scale industrial applications because it does not incorporate machine learning-driven predictive maintenance and is only applicable to single-phase transformers.

Shitole et al. carried out a thorough analysis of numerous IoT-based transformer monitoring systems in 2022, contrasting various sensor technologies and communication protocols [5]. In addition to showing how cloud-based platforms improve remote accessibility, this study highlighted the function of GSM, GPRS, and MQTT in real-time transformer health tracking. This review addressed a wider range of transformer factors, including temperature, vibration, and noise levels, in contrast to Jasper et al. (2023), who specifically addressed oil breakdown voltage. One of the few studies to go beyond threshold-based alerts, it also provided predictive defect detection algorithms. Nevertheless, scaling problems, the dependability of data transmission in remote areas, and sensor durability in challenging climatic conditions persisted as significant challenges in spite of these developments.Real-world implementation was further complicated by false alarms brought on by network instability and cloud data loss.

A real-time monitoring system that tracks load current, voltage, and temperature using a Raspberry Pi and Internet of Things-based sensors was previously reported by Priyanka et al. (2018) [6]. The system ensured timely alerts by effectively implementing SMS-based fault notifications through Twilio cloud services. This study mostly depended on Wi-Fi-based data transfer, which might be less dependable in distant areas, in contrast to Shitole et al. (2022), whose investigation concentrated on a variety of communication technologies. Furthermore, even though the system increased monitoring efficiency, neither the scalability issues for large-scale deployment nor the system's cost-effectiveness in comparison to SCADA-based systems were thoroughly examined. Concerns over the study's viability in actual power networks were also raised by the absence of information on communication dependability in remote locations.

An IoT-based thermal monitoring system employing an ESP8266 and ThingSpeak to measure temperature, humidity, and current was suggested in another 2018 paper by Jamal et al [3]. Its relay-based fault protection and automated cooling methods (DC fan activation) successfully handled overload and overheating situations. This study was less concerned with overall transformer health and more with thermal considerations than Priyanka et al. (2018). But like a lot of early IoT-based monitoring systems, it only used threshold-based warnings and lacked machine learning-driven predictive maintenance. Its design was also restricted to single-phase transformers, which made it unsuitable for extensive power distribution systems.

Despite these efforts, the absence of a comprehensive predictive maintenance framework is a drawback shared by all of the research. Even though real-time monitoring and fault detection have greatly improved, the majority of methods still rely on preset threshold values instead of using AI-driven predictive analytics to anticipate faults before they happen. Furthermore, scalability is still a problem because single-phase transformers are the subject of the majority of research, which limits their use in industrial power systems. Another major problem is network stability in remote locations, where IoT-based communication technologies (Wi-Fi, GSM, GPRS, and cloud networks) frequently have connectivity issues that cause fault warnings to be overlooked or delayed.

By creating a scalable, Internet of Things-integrated transformer health monitoring system that not only allows real-time tracking but also integrates machine learning for predictive maintenance, our research seeks to close these gaps.

This strategy aims to increase power grid dependability, decrease downtime, and prolong transformer lifespan by utilizing sophisticated sensor fusion techniques, AI-driven fault detection, and a strong communication infrastructure.

III. METHODOLOGY

The suggested IoT-based Transformer Health Monitoring and Predictive Maintenance System employs a systematic approach that includes machine learning-driven problem identification, cloud-based monitoring, real-time data sensing, and an intuitive user interface dashboard for display. To guarantee effective transformer monitoring and fault prediction, this method combines a number of technologies, such as cloud computing, predictive analytics, and embedded systems. The block diagram of the workflow of the prototype is visualized in Fig. 1. The methodology is divided into four parts as described below.

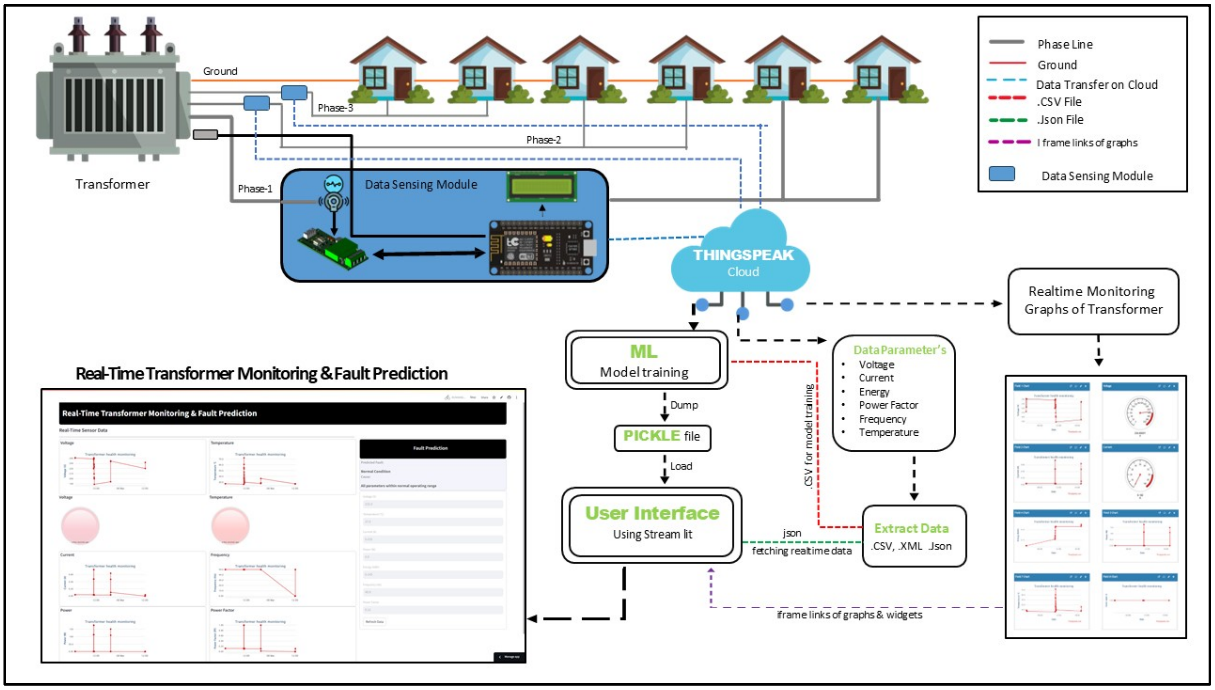

FIGURE 1. Block Diagram of Workflow

1) Part 1 - Hardware Module

To record crucial transformer data like voltage, current, power, frequency, energy, power factor, and temperature, the system uses a number of sensors. Real-time data is continuously gathered by these sensors and shown on an LCD screen that updates every two seconds. Fig. 2 shows the hardware setup for real-time transformer monitoring, including sensors for voltage, current, frequency, power factor, energy and temperature. The LCD displays key electrical parameters on-site monitoring. Additionally, the system has an overload detection mechanism that detects abnormal power levels and promptly notifies users of the malfunction. In order to facilitate remote access and real-time monitoring, the ESP8266 microcontroller unit (MCU) is in charge of sending the sensor data over Wi-Fi to the cloud. The overall hardware module, integrating the data sensing module and the load representation module is depicted in Fig. 3. The incandescent bulb serves as the load, indicating proper power distribution and system functionality.

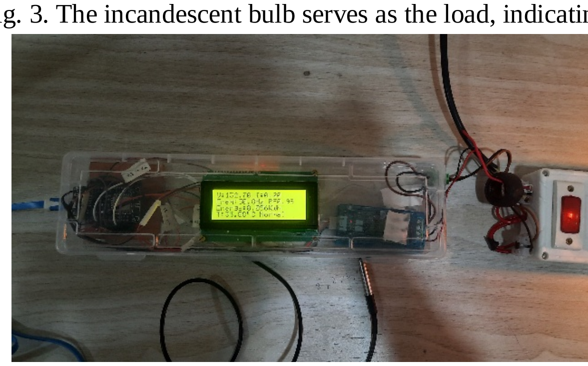
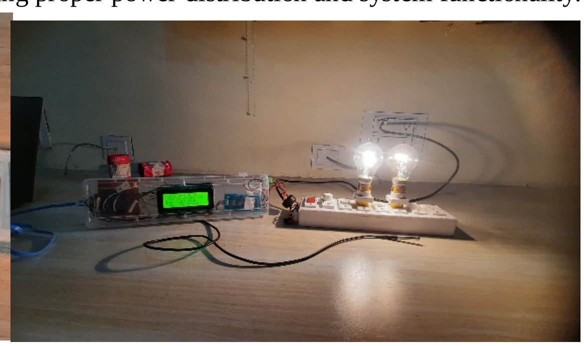

FIGURE 2. Data Sensing Module and LCD DisplayFIGURE 3. Complete Hardware Setup

Transformer stress conditions are simulated using a regulated load to guarantee a realistic examination of transformer health. Fig. 4 demonstrates how an increase in load leads to a decrease in voltage, causing the incandescent bulb to dim, indicating the impact on power distribution. A DS18B20 temperature sensor is also used to simulate temperature changes that are frequently seen when a transformer is operating. Through the imitation of actual transformer behaviors, this configuration enables efficient defect detection. Large-scale applications can benefit from the design's scalability to accommodate three-phase industrial transformers, even if the prototype model created for this study is a single-phase system.The actual load handling setup with sockets and switches for controlling connected loads is illustrated in Fig. 5. A fan regulator is used to vary the voltage for testing different load conditions. The block diagram of hardware module is illustrated in Fig. 6.

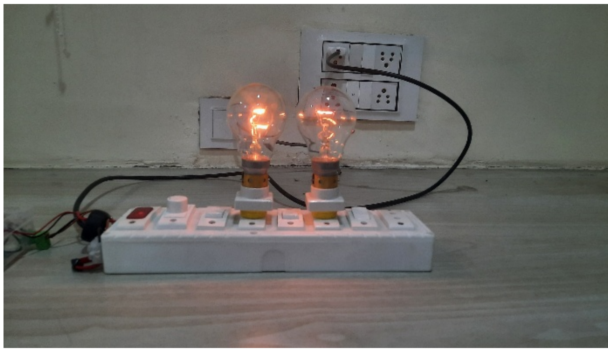
FIGURE 4.Effect of Load Increase on Voltage


FIGURE 5. Load Handling Switch Board

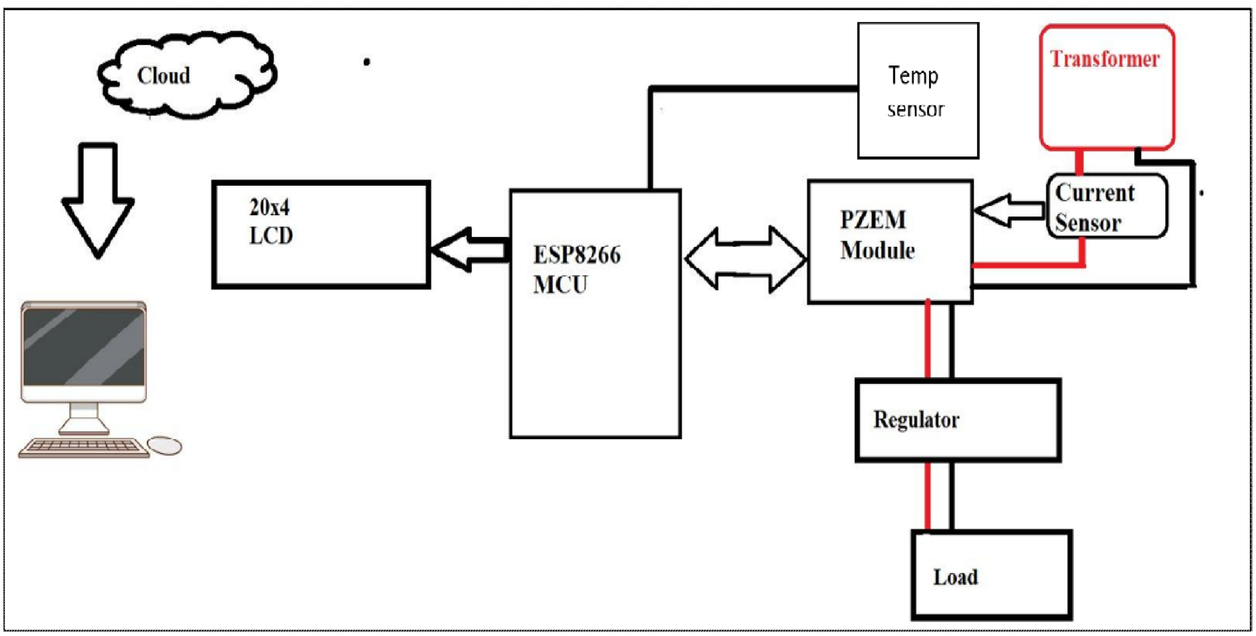

FIGURE 6.Block Diagram of Hardware Module

2) Part 2 - Cloud Platform

In order to collect and monitor data in real time, the cloud platform is essential. Every 30 seconds, the system updates the data on the ThingSpeak cloud platform with real-time sensor readings. Fig. 7shows the main channel interface with the Channel ID, private and public dashboard views, API keys access, data import/export options, and real-time parameter graphs and widgets for transformer health monitoring. Fig. 8 displays the overall graphical visualization of real-time sensor data, including voltage, current, power, energy, frequency, power factor and temperature trends. Continuous tracking and analysis of transformer performance is made possible by the storage of all recorded parameters in a specific ThingSpeak channel called "Transformer Health Monitoring."

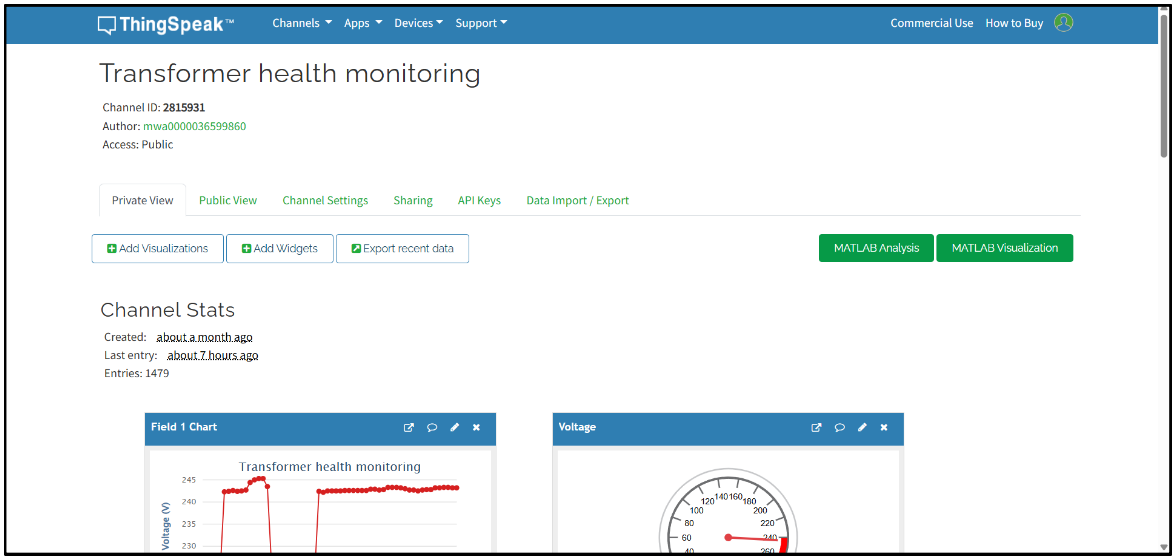

FIGURE 7. ThingSpeak Channel Dashboard

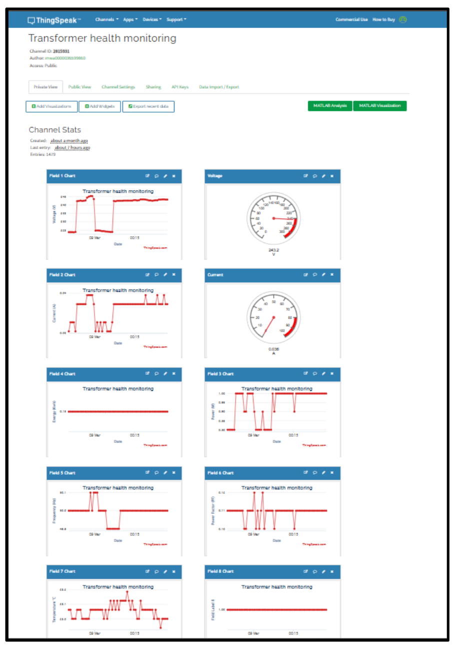

FIGURE 8. ThingSpeak Graphical Representation

TABLE 1.Comparison of Prototype and Real Transformer Parameters

PARAMETER	PROTOTYPE SOURCE	REAL TRANSFORMER EQUIVALENT
Voltage	Grid (same as transformer)	Transformer output voltage
Frequency	Grid (fixed)	Grid Frequency
Current	Load- dependent	Phase Current
Temperature	Simulated Via External Heating	Oil/Core Temperature

The cloud-based monitoring system keeps an organized archive of past sensor data to guarantee accessibility and dependability. This makes early fault detection and long-term performance analysis easier. Table 1 presents a comparative analysis of parameters between the prototype model and a real transformer, highlighting their respective data and equivalent values.

The ThingSpeak platform improves the usability of the monitoring system by integrating interactive visualization features in addition to enabling remote monitoring. Later, machine learning techniques are used to process and analyze the cloud-stored data in order to spot faults in advance.

3) Part 3- Machine Learning Model

Several machine learning models are trained using previous sensor data that has been exported in CSV format to improve fault detection accuracy. Predictive maintenance analysis and live fault categorization are made possible by the trained models receiving real-time sensor inputs in JSON format. To find the best method for fault detection, the system tests a number of machine learning techniques, such as Random Forest, XGBoost, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and LightGBM. With the maximum accuracy of 99.2%, the Random Forest classifier is the recommended model for fault prediction. Fig. 9 illustrates the step-b-step workflow of the achine learning approach, covering data preprocessing, model training, fault classification, and real-time fault prediction.

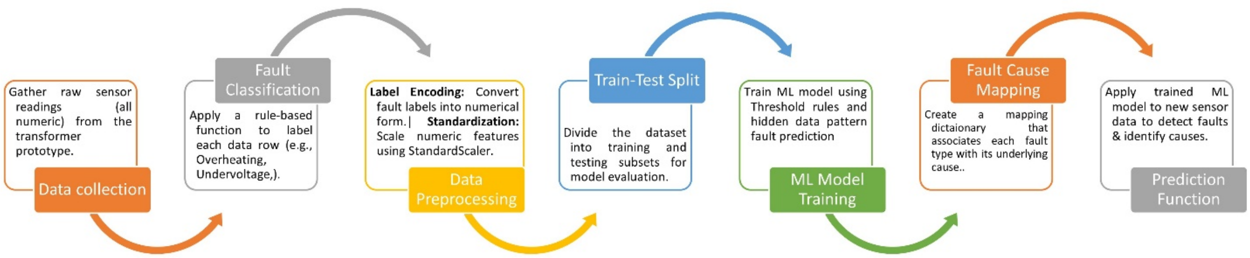

FIGURE 9. Machine Learning Workflow

Analyzing input data including voltage, current, power, energy, frequency, power factor, and temperature is how the fault detection model works. Table 2 outlines the classification of transformer conditions based on predefined threshold values, categorizing them into different faut types.Using preset threshold values, the model is trained to categorize various failure types and identify their root causes. For example, the system will identify the failure as an overvoltage and overheating problem if it detects a voltage level above 240V and a temperature above 90°C. Pickle and Joblib are used to deliver the trained model, guaranteeing quick execution and smooth monitoring system integration.

TABLE 2.**Fault Classification Based on Threshold Conditions**

CLASSIFICATION	CONDITION
Overheating & Overvoltage	Voltage > 240V and Temperature > 90°C, indicating critical risk from both overvoltage and excessive heat.
Overvoltage	Voltage > 240V (even with normal temperature), suggesting potential grid surge or regulator issues.
Undervoltage	Voltage < 180V, pointing to insufficient supply or overload condition
Normal	Applied if none of the above conditions are met, indicating safe operational parameters

The trained machine learning model is hosted on GitHub to provide easy sharing, deployment, and future enhancements, hence improving user accessibility. For convenience and version control, the repository includes the predictive maintenance scripts and the machine learning model under the MajorProject.py file.

4) Part 4- User Interface Dashboard

Streamlit is used in the development of the real-time monitoring user interface (UI), which offers an interactive and dynamic dashboard. The user interface displays real-time sensor data through aesthetically pleasing graphs and widgets that are retrieved straight from the ThingSpeak API. Additionally, it incorporates the previously taught machine learning model to categorize errors and provide the associated causes instantly. Fig 10. Displays the UI Code Workflow.

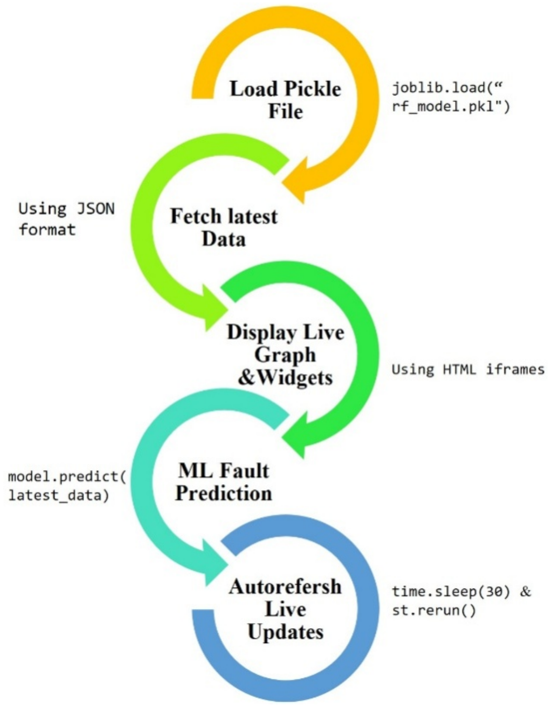

FIGURE 10. UI Code Workflow

The dashboard's primary features include interactive elements that enable users to effectively evaluate transformer health, auto-refresh functionality every 30 seconds, and real-time depiction of voltage, current, power, and temperature trends. By providing remote dashboard access through a web link, the Streamlit Community Cloud removes the need for manual intervention and guarantees ongoing monitoring. Furthermore, anytime the system is modified, automatic updates are guaranteed thanks to the interaction with GitHub.

Collaboration and future improvements are made easier by the availability of the UI dashboard code in the ui_app.py file on the GitHub repository. Predictive maintenance, fault detection, and real-time data monitoring work together to create a comprehensive transformer health assessment system that increases operational reliability and reduces unplanned failures.

IV. RESULTS AND DISCUSSIONS

Using high-precision sensors, the Data Sensing Module in the suggested system effectively records key transformer data such as voltage, current, power, energy, frequency, power factor, and temperature. Accurate monitoring is ensured by the LCD screen's real-time updates every two seconds. Furthermore, the technology provides immediate problem detection by detecting overload circumstances depending on power levels. The ESP8266 microcontroller unit (MCU) securely sends sensor data over Wi-Fi to the ThingSpeak Cloud to facilitate remote monitoring.

A key component of real-time data collection and monitoring is the cloud platform. To ensure accuracy, ThingSpeak updates every 30 seconds based on real-time sensor readings. For analysis and visualization, the data is kept in a specific ThingSpeak Channel ("Transformer Health Monitoring"). Fig. 11 illustrates ThingSpeak page displaying the channel ID. Transformer stress conditions are simulated using a controllable load, and realistic fault analysis is provided by the DS18B20 sensor, which simulates temperature changes. The single-phase prototype model is intended to be scalable to three-phase industrial systems and effectively illustrates the viability of IoT-based transformer monitoring.

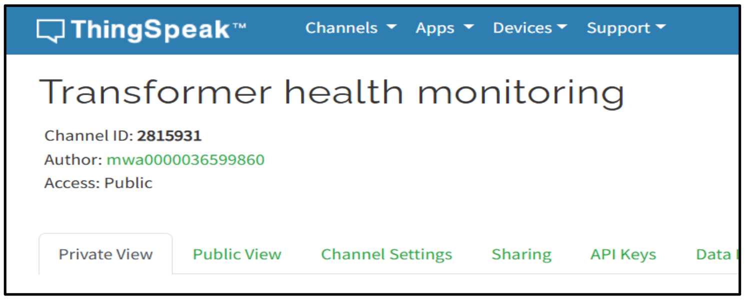

FIGURE 11.ThingSpeak Page Displaying the Channel ID

Historical sensor data is produced in CSV format for training different machine learning models, and real-time defect detection is done using JSON format for machine learning data processing and fault detection. Fig 12 demonstrates accessing JSON, XML, and CSV files from ThingSpeak. The system uses HTML iframes to show real-time updates through embedded interactive graphs and widgets. Screenshot of the HTML iframe for embedding live grapghs is shown in Fig. 13. Live sensor values are retrieved via a JSON API for the user interface display, guaranteeing immediate fault classification and prediction. For collaboration and version control, the machine learning model and prediction scripts are kept on a GitHub repository. The Github repository link is: https://github.com/Transformer-Health-Monitoring/Transformer-Health-Monitoring---Fault-Prediction/blob/main/ui_app.py and the ThingSpeak channel link is: https://thingspeak.mathworks.com/channels/2815931/private_show

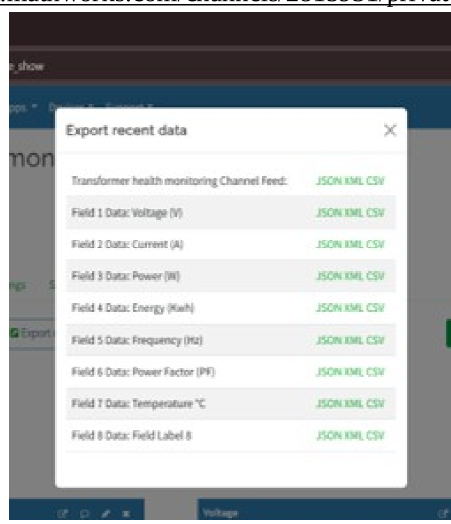

FIGURE 12.Accessing JSON, XML, and CSV Files from ThingSpeak

FIGURE 13.Screenshot of the HTML iframe for Embedding Live Graphs

Random Forest, XGBoost, SVM, KNN, and LightGBM were among the algorithms tested during the Machine Learning Model evaluation phase.

Table 3 presents the different ML models trained for fault classification and their corresponding accuracy after training. With a 99.2% fault classification accuracy, the Random Forest classifier was chosen as the top-performing model. In order to forecast fault types and their causes, the system's Predicted Fault and Cause Function examines input data such as voltage, current, power, energy, frequency, power factor, and temperature. For instance, when the voltage rises above 240V and the temperature rises above 90°C, an overheating and overvoltage fault is set off. Table 4 shows sensor readings from the data-sensing model as input and the ML model's predicted fault type and cause based on threshold rules and pattern learning. Pickle and Joblib are effectively used to deploy the trained model, guaranteeing dependable and quick execution.

TABLE 3.Machine Learning Models and Their Respective Accuracy

Model	Accuracy (%)
Random Forest	99.2%
XGBoost	97.5%
SVM	90.8%
KNN	88.3%
LightGBM	93.6%

TABLE 4.ML Model Input and Predicted Fault Output

Input							)utput	
Voltage	Current	Power	Energy	Freq	Power factor	Temp	Fault Type	Cause
250	0.1	20	0.02	50	0.8	95.5	Overheating & Overvoltage	High voltage causing excessive heat or cooling system failure
245	0.09	18	0.018	49.99	0.75	85	Overvoltage	Grid surge or faulty voltage regulator
150	0.085	14.4	0.015	49.98	0.62	95.3	Undervoltage	Grid instability or transformer overload
220	0.08	16	0.017	50	0.85	70	Normal	All parameters within normal operating range

Streamlit serves as the foundation for the UI Dashboard, which offers an intuitive interface for real-time monitoring. Fig 14 displays the screenshot of the UI Dashboard webpage and the link to the live dashboard is: https://transformer-health-monitoring---fault-prediction-p9vkv89ubje4t.streamlit.app/ . It displays changes in voltage, current, and power dynamically and retrieves real-time sensor data from the ThingSpeak API. Using the pre-trained machine learning model, the user interface incorporates fault prediction, fault classification, and comprehensive cause analysis. To guarantee constant updates, the dashboard automatically refreshes every 30 seconds. Streamlit Community Cloud has successfully implemented the system, enabling remote access over a web link. Automatic updates, free and serverless hosting, and easier deployment are guaranteed by the interaction with GitHub.

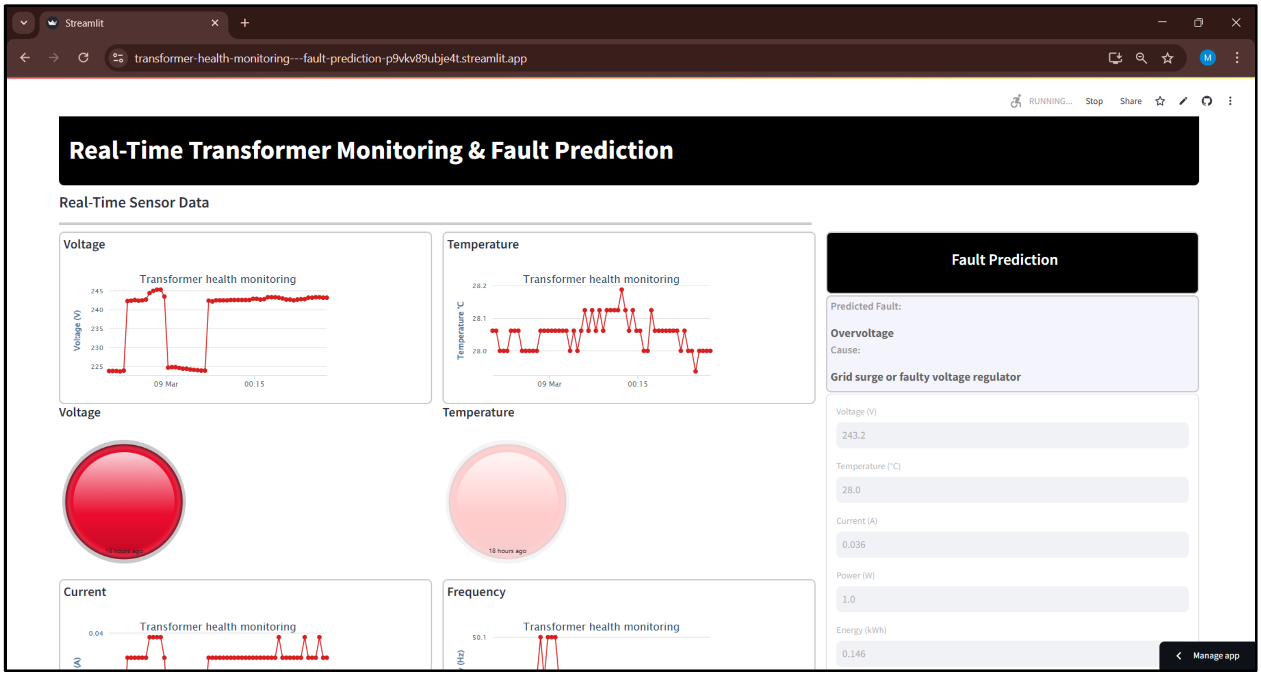

FIGURE 14.Screenshot of the UI Dashboard Webpage

To sum up, the suggested Real-Time Transformer Monitoring & Fault Prediction system effectively integrates cloud computing, machine learning, and the Internet of Things to provide ongoing transformer health evaluation. Transformer reliability is increased, maintenance expenses are decreased, and unplanned failures are decreased by combining remote monitoring, fault prediction, and real-time alarms. Edge computing may be used in future improvements to provide longer scalability and faster processing for industrial applications.

V. CONCLUSION

This paper presents an IoT-integrated transformer health monitoring and predictive maintenance system, leveraging advanced communication technologies such as GSM, LoRa, Zigbee, and Bluetooth to enable real-time condition assessment. By incorporating multi-sensor fusion and AI-driven predictive analytics, the proposed system enhances fault detection, reduces downtime, and extends transformer lifespan. The reviewed studies highlight the effectiveness of IoT in improving reliability, efficiency, and automation in power distribution networks. Future work can focus on integrating edge computing and machine learning for further optimization, ensuring a more resilient and intelligent power grid.

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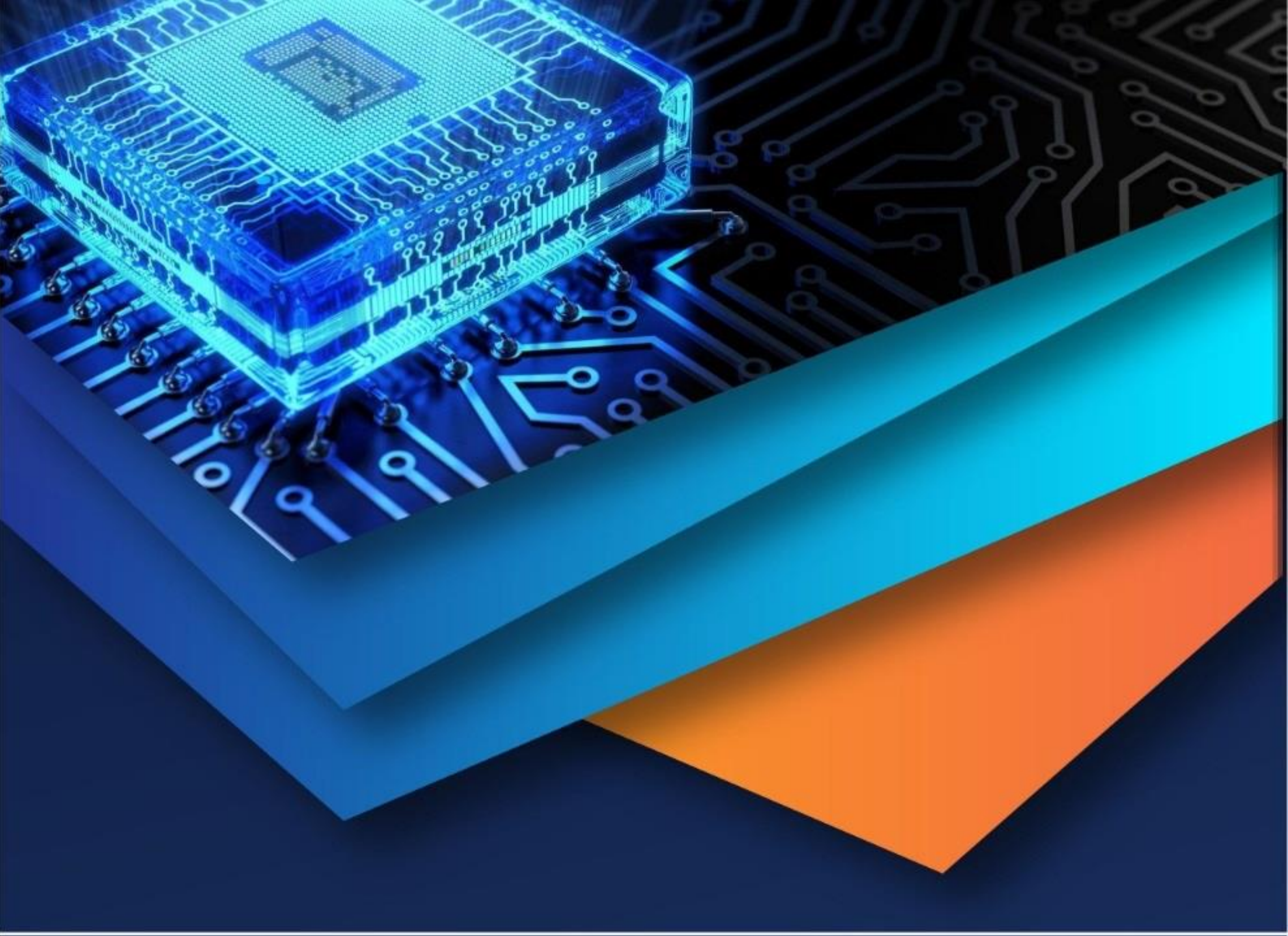

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