IoT-Enabled Wireless Communication Monitoring and Fault Diagnosis for Transformer Oil Condition Using Machine Learning

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Abstract—**Distribution transformers play a critical role in ensuring uninterrupted power supply, yet their performance is often compromised by undetected internal faults and oil degradation. This paper presents the development and validation of an intelligent, low-cost, and real-time monitoring and fault diagnosis system for distribution transformers by integrating Internet of Things (IoT) technologies with Artificial Intelligence (AI)-based classification algorithms. The system employs wireless sensors to continuously monitor key operational parameters, including temperature, light intensity, and oil level, with data transmitted via ZigBee modules to a central LabVIEW interface and secure cloud platform for real-time visualization, control, and remote access. To ensure reliable communication, the proposed framework incorporates robust data transmission protocols and minimal latency for continuous monitoring. For intelligent fault classification, Decision Tree (DT) and Multi-Layer Perceptron (MLP) classifiers were used. Experimental results demonstrate that the DT model achieved a training accuracy of 95.9% and testing accuracy of 94.5%, outperforming MLP with 94.9% and 90.9%, respectively. The DT classifier also yielded superior F1−Score (0.931) and specificity (0.954) across multiple transformer oil condition classes. The results confirm the effectiveness of the proposed hybrid IoT-AI solution in reliably detecting and classifying oil condition anomalies for timely maintenance actions and operational safety. The system offers a scalable and cost-effective alternative to conventional Supervisory Control and Data Acquisition (SCADA) and PLC-based monitoring, with potential for integration into predictive maintenance frameworks for smart grid applications.**

Keywords—**distribution transformer, Internet of Things (IoT), oil monitoring, machine learning**

I. INTRODUCTION

Wireless communications are widely used within remove monitoring applications due to its fast-based nature of processing [1−3]. Remote monitoring of distribution transformers is an important task to the power management department and other related works [4, 5].

This monitoring is usually done manually or experimentally using an expensive Programmable Logic Controller (PLC) and Supervisory Control and Data Acquisition (SCADA) systems [6−10]. There are many monitoring strategies, condition monitoring, and fault detection using IoT technologies [11], machine Learning models [12], electricity theft detection and monitoring in power grids [13], oil level detection monitoring [14], localized transformer monitoring (Real-time) [15], and transformer fault detection based on transformer Windings [16]. In the era of edge computing, it is highly desirable to have an intelligent monitoring system and a reliable control system for the entire system. This procedure is to be achieved by the application of Internet of Things (IoT) technologies [17−20].

IoT is a network of physical objects with electronics, software, sensors, actuators, and network connectivity that can identify [21]. Monitoring and fault detection using IoT devices is the most optimum method when it comes to monitoring many transformers from a single control center. IOT devices like GSM/GPS modules, controllers like Arduino Mega, Raspberry Pi, and communication modules like ESP32 and ESP8266 can be used [22]. These devices are further integrated with a suite of sensors, which monitor various parameters of the transformer: Temperature of the core, oil, and winding defects, and the electrical parameters like primary and secondary winding currents, Load power, etc. To regulate certain parameters, we have actuators which receive commands from the control center (could be a mobile phone, Computer, or Terminals) through the IoT devices [23]. During the transformer operation, various factors affect its performance, and it's crucial to monitor these parameters to avoid an efficiency drop. The sensors are constantly monitoring these parameters and feeding the data to the control center through the communication devices (ESP8266, ESP32, SIM 800/900 and protocols (MQTT, Wi-Fi, ZIGBEE, Bluetooth) [24, 25]. The controllers like Raspberry Pi, Arduino Mega, and others control these

sensors and other devices like auxiliary communication devices and ports (USB, RS-232, UART, etc.).

The data sent through the communication devices travels through a secure network established for that purpose and data is usually stored, compared, and modified using a database. These databases are stored in secure locations, usually in the control centers. The technician/operator at the control center monitors the data coming from many transformers and responds according to the situation. For example, one of the transformers has an issue with the oil temperature, and certain gases have accumulated, which need to be regulated. The operator sends a command to the transformer monitoring system to open a valve to let the gases out of the oil chamber [26]. The transformer monitoring dataset can be used to classify defects using machine learning algorithms. Multilayer neural networks and support vector classification are the algorithms most employed. These learning techniques are used to create models from the available data.

Recent advances in IoT technology have enabled real-time transformer condition monitoring through the integration of low-cost sensors, wireless modules like ZigBee, and expert systems powered by machine learning. By combining thermal analysis with intelligent classification techniques, these systems offer promising solutions for early fault diagnosis, especially in resource-limited environments. Platforms such as LabVIEW further enhance the human–machine interface, enabling operators to interact seamlessly with live data streams for predictive maintenance decisions.

Despite these developments, the literature remains fragmented in several key areas. Most notably, comprehensive evaluations of the long-term sustainability, interoperability, and regional adaptability of IoT-based transformer monitoring systems are limited. While prior studies emphasize the technological feasibility of IoT systems, less attention has been given to their practical deployment constraints, integration scalability, and comparative advantage over traditional fault detection mechanisms. Additionally, limited insight is available regarding the implementation challenges encountered in real-world settings—particularly those involving heterogeneous sensor networks and diverse transformer types. This study aims to address these gaps by presenting a comprehensive review and practical implementation of an IoT-enabled transformer oil monitoring system, designed for fault detection through machine learning-based diagnosis. The key contributions of this work are as follows:

- Design and implementation of an IoT-based transformer monitoring system incorporating ZigBee communication, multiple sensor nodes, and a LabVIEW user interface to track oil verification and temperature.
- Integration of machine learning classifiers into the monitoring framework to perform intelligent fault diagnosis based on real-time thermal and fluid condition data.
- Systematic review and synthesis of existing literature focusing on sensor fusion, microcontroller

configurations, communication protocols, and deployment challenges in IoT-based transformer systems.
- Discussion of operational barriers and scalability concerns for cost-effective implementation strategies for utilities in developing or resource-constrained environments.

The remainder of this paper is organized as follows: Section II presents the literature review, and Section III describes the system architecture and hardware components, as well as the software integration and communication protocols of the methodology. Section IV outlines the machine learning framework and data preparation. Section V discusses the experimental results and model evaluations. Finally, Section VI concludes the study with key findings and future directions.

II. LITERATURE REVIEW

In the past few years, smart monitoring of distribution transformers has become increasingly prevalent. Authors and maintenance specialists are exploring diverse strategies to improve the dependability and efficacy of maintenance. This section provides a literature review in this field, highlighting key studies and techniques. This appears to be the inaugural effort to amalgamate AI and IoT technology for real-time transformer problem detection.

In 2021, Kwarteng *et al.* [27] the health condition index of distribution transformers was assessed based on variations in phase current values, oil level, moisture content, and load capacity, all of which are detected using sensors. Arduino has been chosen as the processor for transferring sensed data, while the Blynk App has been designated as the IoT platform for presenting the received data. Odongo *et al.* [28] executed an IoT platform utilizing LoRa WAN for the surveillance of distribution networks. The study was conducted in Nakuru County, Kenya, using an active distribution network managed by Kenya Power Company. When a failure occurs in the distribution network, a trigger is activated at the network monitoring center.

Okoli *et al.* [29] worked to monitor the characteristics of distribution transformers by transmitting data at specified time intervals, indicating the status of the transformer to facilitate early fault detection and rapid fault response. These sensors were employed to assess the transformer's condition to facilitate prompt fault identification. The sensor outputs were transmitted to the microcontroller for processing. The microcontroller calculates the power of the connected load based on the measured voltage and current. Venumadhav *et al.* [30] presented the design and execution of a system capable of real-time monitoring of the operational parameters of a distribution transformer. The characteristics encompass the load current, voltage level of the transformer oil, and environmental conditions such as temperature and humidity. Various sensors measure a transformer's primary parameters, including voltage, current, oil level, and temperature. Utilizing a Wi-Fi module and Thingspeak software, the acquired data is transmitted to a

microcontroller, where it is verified against specific specifications before being forwarded to an IoT web server.

Sudha *et al.* [31] employed machine learning methods to identify typical short circuit defects in distribution transformers. The test dataset for the short circuit resistance of a 2 KVA distribution transformer is utilized for the machine learning technique. This data is examined using several feature extraction and classification approaches. The appropriate machine learning approach for determining the short circuit resistance in a 2 KVA distribution transformer is the K-Nearest Neighbour algorithm. Zheng *et al.* [32] presented a hybrid deep learning model that integrates CNN and LSTM to autonomously identify the partial discharge patterns of power transformers, utilizing dual-channel pictures formed by PRPD and PRPS as inputs. The CNN inside the model architecture is intended to capture the spatial interaction across channels, whilst the LSTM is employed to obtain the temporal information from the spectrum. Table 1 provides a comparative summary of recent studies on transformer condition monitoring, highlighting their methodologies, sensor configurations, communication protocols, and the role of AI/ML techniques, with the present study positioned as a unified and scalable IoT–ML solution.
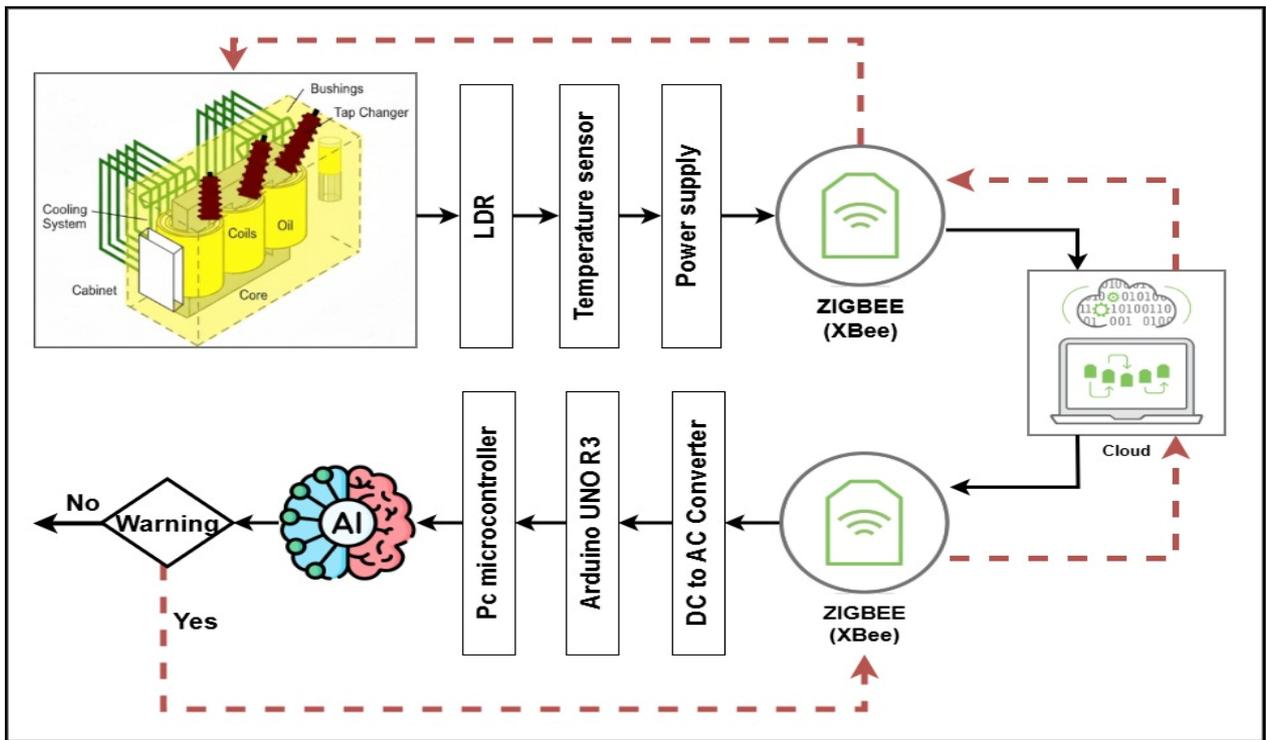

Fig. 1. The framework of the proposed system for smart monitoring of electrical distribution transformer using IoT and ML technologies.

TABLE I. LITERATURE SUMMARY AND CONTRIBUTION

Ref.	Approach	Communication	AI/ML Technique	Contribution
[27]	Arduino + Blynk-based IoT monitoring	Wi-Fi	None	Developed low-cost platform for basic condition monitoring
[28]	LoRaWAN-based IoT monitoring	LoRaWAN	None	Real-world deployment in a live distribution network
[29]	Voltage-current monitoring with power estimation	Not specified	None	Facilitated early fault detection via load power tracking
[30]	Real-time monitoring with IoT web server	Wi-Fi + ThingSpeak	Rule-based validation	IoT-based environmental and electrical parameter monitoring
[31]	ML-based short circuit fault detection	Not applicable	KNN	Used ML to estimate resistance and classify faults
[32]	Deep learning for partial discharge detection	Not applicable	CNN + LSTM	Extracted spatial-temporal features for advanced diagnostics
This Study	IoT–ML integrated real-time oil monitoring system	ZigBee, LabVIEW	Supervised ML classifiers	Unified system with real-time fault diagnosis, scalable & cost-effective

III. METHODOLOGY

The proposed system comprises multiple stages for monitoring the transformer oil, which is vital for the transformer's operation, and controlling it by implementing suitable measures in the event of abnormal

operation. In such cases, the system will send a warning signal. Conversely, if the operation is normal, the system will continue monitoring without issuing alerts. The suggested system's general framework is depicted in Fig. 1, where the system first starts by connecting different sensors (LDR, temperature sensor, and power source) to the transformer. The data from these sensors is transferred wirelessly using the ZigBee communication module and sent via the cloud to a microcontroller (Arduino UNO R3). At this stage, data processing and analysis begin using Machine Learning (ML) and Deep Learning (DL) techniques based on the previously trained model. If the results classify the transformer oil condition as Good, the system continues normal operations. However, if the oil condition is classified as Not Bad, Poor, or Very Poor, the microcontroller triggers an alert signal back through ZigBee, which is relayed to the transformer via the cloud for appropriate maintenance action. This real-time feedback loop enables continuous monitoring, predictive maintenance, and remote control of electrical transformers, ultimately improving system reliability and reducing the risk of transformer failure.

TABLE II. EXPERIMENTAL COMPONENTS

Component	Function	Key Specifications	Role in System
Temperature Sensor (FBG-PCF)	Monitors transformer oil temperature to detect overheating and insulation degradation	High sensitivity to temperature changes	Identifies overheating conditions and predicts insulation failure
LDR Sensor	Detects ambient light intensity levels within the transformer environment	Light-dependent resistance variations	Monitors environmental lighting conditions and anomalies
Power Supply (AMS1117)	Provides stable voltage for sensors and communication devices	1A output, 1V input-to-output differential, compact design	Ensures reliable and safe operation of all transmitter components
ZigBee (XBee Module)	Enables wireless data transmission between transmitter and cloud/microcontroller	2.4 GHz frequency, 250 kbps rate, up to 1500 m range, 128-bit encryption	Facilitates secure and efficient wireless communication

A. Transmitter Section

The transmitter section serves as the first stage of the proposed system, where key data about transformer health is collected. It comprises sensors for measuring vital operational parameters, a stable power supply to ensure consistent performance, and a ZigBee module for reliable wireless communication. These sensors continuously monitor oil temperature, environmental light conditions, and other physical factors affecting transformer performance. The transmitter acts as the bridge between the transformer and the data analysis unit by capturing real-time data and sending it to the cloud, where it is further processed and evaluated by the microcontroller and machine learning models.

To provide a clear and concise overview of the transmitter section components, Table II summarizes the essential hardware elements, their specifications, and their respective roles in the system. This tabular presentation replaces the need for lengthy descriptions of each component while allowing for straightforward reference during implementation or replication of the proposed monitoring setup.

B. Cloud Server

Cloud is a platform that uses to store and accesses data via the internet in real-time. In this experiment, we use the Cloud services of Thingspeak to store and upload IoT data to the Cloud. We can also perform analysis, visualize, or aggregate data in real-time [33]. In Thingspeak, we have to create a channel having different fields to store and represent data coming from different sensors through the internet. We create two fields to connect with the following two sensors: oil level measurement, and the temperature of the oil as shown in Fig. 2.
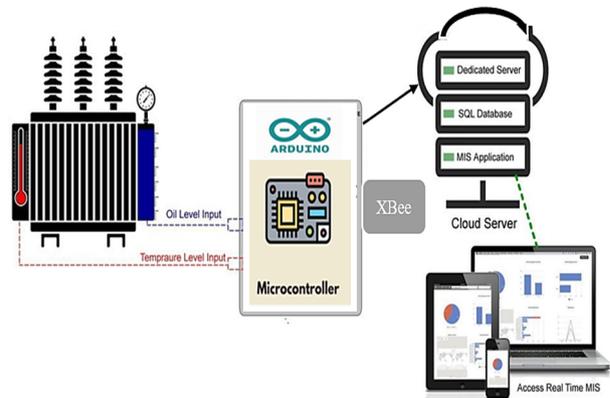

Fig. 2. Temperature and oil level measurement using IoT sensors.

C. Receiving Section

Data was acquired using a UNO R3 Arduino-style device. It is able to read input and convert it to an output; Arduino is an open-source electronics platform. A microcontroller board based on the ATmega328P, the Arduino card type UNO R3 contains an ICSP header, a reset button, six analog inputs, a USB port, a power jack, a 16 MHz quartz crystal, and fourteen digital input/output pins, six of which can be used as PWM outputs. As demonstrated in Fig. 3, It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with an AC-to-DC adapter or battery to get started.

Low-power CMOS 8-bit RISC microcontrollers named Atmega16 are available. Using an SPI serial link, the on-chip ISP Flash enables in-system reprogramming of the program memory. The voltage range at which the Atmega16 can function is 2.0V to 5.0V. It provides four 8-pin ports, for a total of 32 I/O pins. There are two primary components to the software implementation of this research project. The Atmega16 microcontroller on the receiving end is used for the software implementation. The source code, written in the C language, was created and compiled using the WinAVR software development tool

to program the microcontrollers [34]. The programming was all done in C, even though inline assembly was an option. To help with sporadic maintenance and improvement in the future, the source code has been commented. This code has been compiled and loaded into the microcontroller using the PonyProg serial device programmer [35]. The software implementation on the receiving side is MATLAB-based.

Fig. 3. Arduino UNO R3.

Parameters are processed and recorded using-in16-channel Analog to Digital Converter (ADC) of the embedded system in the system memory. Due to the ADC, the system will take more time to process and communicate the data. By connecting the necessary pins, the ZigBee transceiver and Atmega16 microcontroller receiving can be interfaced as depicted in Fig. 4, because both interact over a serial UART interface, their interface may be completed very simply. To meet the requirements of the ZigBee, a few things need to be taken into account. While ZigBee is meant to run at 3.3V, whereas Atmega16 microcontrollers run at higher voltages. Voltage regulation can be easily accounted for by using a LM317 voltage regulator.
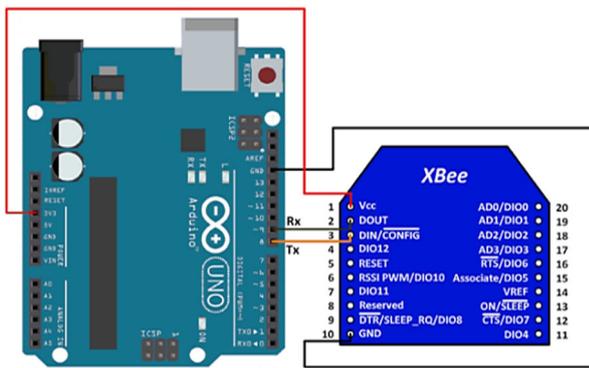

Fig. 4. The interface of the XBee transmitter unit with the Microcontroller (Atmega16) receiving unit.

D. Dataset Description and Preprocessing

The dataset used in this study was obtained from real transformer units operated and tested at the Diyala State Company for Electrical Industries (Iraq). The data were collected as part of an ongoing experimental program on power and distribution transformers conducted by the company's quality control and maintenance departments. Measurements were recorded from various transformer types available at the facility, in addition to several external transformer samples that were brought in for oil-quality assessment.

The dataset comprises 2,000 records collected over multiple measurement sessions covering different temperature conditions (from 0°C to 80°C). Each record represents one oil sample measurement containing key optical and electrical characteristics used to evaluate transformer oil degradation. The raw data were acquired from Fiber Bragg Grating (FBG-PCF) optical sensors connected to the monitoring circuit, and readings were extracted from the original Excel data file provided by the laboratory instrumentation.

Table III summarizes the principal parameters included in the dataset. The features include wavelength-based measurements (centroid, peak, and offset), Full-Width at Half-Maximum (FWHM), and Optical-Signal-to-Noise Ratio (OSNR), along with corresponding temperature, Light Intensity (LDR), and power readings. These parameters collectively describe the physical and optical behavior of transformer oil under varying operational conditions.

TABLE III. DATASET PARAMETERS AND DESCRIPTION

Parameter	Unit	Description
Centroid Wavelength	nm (air)	Central wavelength of optical signal, representing oil refractive index variation
Peak Wavelength	nm (air)	Maximum reflected wavelength used to track temperature and contamination shifts
Peak Level	nW	Optical power at the detected peak
FWHM	pm (air)	Full width at half maximum, indicating spectral broadening due to oil degradation
ΔPeak Position	nm (air)	Deviation of peak wavelength from baseline reference
Offset Peak Position	nm (air)	Difference between measured and reference wavelengths
Temperature	°C	Measured oil temperature for each sample (0 – 80 °C)
Level	dBm	Recorded optical signal intensity
Noise	dBm	Noise level of optical signal used for OSNR computation
OSNR	dB	Optical signal-to-noise ratio, a quality indicator for oil transparency and condition

E. Artificial Intelligence (AI)

AI plays a crucial role in the proposed monitoring system by enabling intelligent fault diagnosis and predictive maintenance [36−40]. Machine learning is an extension of AI and uses algorithms to achieve its goals [41−46]. Many applications of interest have adopted these AI-based algorithms [47−49]. In this study, two Machine Learning (ML) algorithms were employed: Multi-Layer Perceptron (MLP) and Decision Tree (DT). The MLP, a type of artificial neural network, is effective for handling complex, non-linear relationships between input features and outputs, making it suitable for continuous monitoring data. Conversely, the DT algorithm provides a transparent and interpretable model for classifying oil conditions into predefined categories. The DT and MLP algorithms were selected for their complementary advantages—DT offers transparent and interpretable decision boundaries ideal for real-time fault diagnosis, while MLP efficiently captures

non-linear relationships between sensor data and oil condition states [50]. These algorithms analyze data collected from sensors connected to the transformer, such as oil temperature, light intensity, and power levels, to determine the health status of the transformer oil. The overall aim is to predict whether the oil condition is Good, Not Bad, Poor, or Very Poor, facilitating timely intervention to prevent failure.

To ensure accurate and efficient model performance, several parameters were selected and optimized during the model training stage. These parameters include data preprocessing methods, feature selection, and algorithm-specific hyperparameters. Table 4 summarizes the main parameters used in training and validating both algorithms. This includes dataset size, the number of training and testing samples, learning rates, maximum tree depth, and other key settings that influence model performance. By clearly outlining these parameters, the table provides a reproducible reference for researchers and practitioners aiming to replicate or extend the proposed approach. The selected features—temperature, oil level, LDR, and power—were chosen because they represent the most critical and directly measurable indicators of transformer oil health using low-cost, IoT-compatible sensors, ensuring real-time monitoring with minimal hardware complexity and high reliability.

TABLE IV. TRAINING AND VALIDATION PARAMETERS OF ML MODELS

Parameter	Multi-Layer Perceptron (MLP)	DT
Dataset Size	2,000 records	2,000 records
Training/Testing Split	70% / 30%	70% / 30%
Number of Features	5 (Temp., Load, Oil Quality, LDR, Power)	5 (Temp., Load, Oil Quality, LDR, Power)
Activation Function	ReLU	Not Applicable
Optimizer	Adam	Not Applicable
Maximum Tree Depth	Not Applicable	5
Learning Rate	0.001	Not Applicable
Output Classes	4 (Good, Not Bad, Poor, Very Poor)	4 (Good, Not Bad, Poor, Very Poor)

TABLE V. CROSS-VALIDATION AND HYPERPARAMETER TUNING SUMMARY

Item	MLP	DT
CV protocol	Stratified 5-fold (nested grid search)	Stratified 5-fold (nested grid search)
Search space	max_depth {3,4,5,6,8,10}; min_samples_split {2,5,10,20}; min_samples_leaf {1,2,4,6,8}; criterion {gini, entropy}	Hidden layers {(64), (64,32)}; dropout {0.0, 0.2}; L2 {0, 1e-4, 1e-3}; batch {32, 64}; epochs ⩽ 100 (early stopping, patience 10); Adam; LR = 0.001; ReLU
Selected config	max_depth = 5; min_leaf = 4; min_split = 5; criterion = gini	layers = (64,32); dropout = 0.2; L2 = 1e-4; batch = 32; epochs ⩽ 100 (early stopping)
Overfitting controls	Pre-pruning (depth/leaf/split), CV	Early stopping, dropout, L2, CV
CV accuracy (mean ± SD)	0.938 ± 0.012	0.923 ± 0.017

Item	MLP	DT
Significance (paired t-test on folds)	DT > MLP, $p < 0.05$	—

The detailed training protocol, validation approach, and tuned hyperparameters for both DT and MLP models are summarized in Table V, ensuring methodological transparency and reproducibility of the AI implementation. The decision-making process of the proposed classification system is visually represented in Fig. 5, which shows the flow of the DT model used to categorize transformer oil condition. The figure begins with raw sensor data, such as transformer oil temperature, LDR values, and power supply readings, and systematically branches through decision nodes. Each split represents a condition based on threshold values, leading to one of the four final classifications: Good, Not Bad, Poor, or Very Poor. By using this hierarchical decision structure, operators and technicians can easily interpret the reasoning behind the classification results, making it a practical tool for real-time diagnostics and maintenance planning.
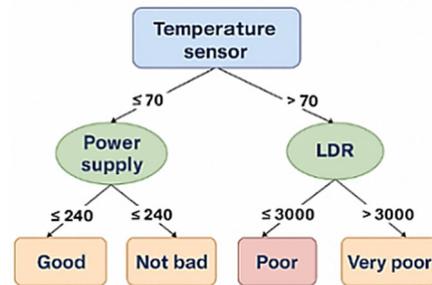
Fig. 5. Proposed algorithm for classification of transformer oil.

IV. EXPERIMENTAL SETUP

A. Hardware Part

The hardware implementation of the proposed system involves assembling and integrating all components required for the transmitter unit, which forms the foundation of the IoT-based transformer monitoring setup. Fig. 6 illustrates the overall monitoring framework using IoT technologies, while Fig. 7 focuses specifically on the transmitter unit described earlier in Section III. These components are mounted on a Printed Circuit Board (PCB), which serves as the platform for interconnecting and securing the electronic elements.
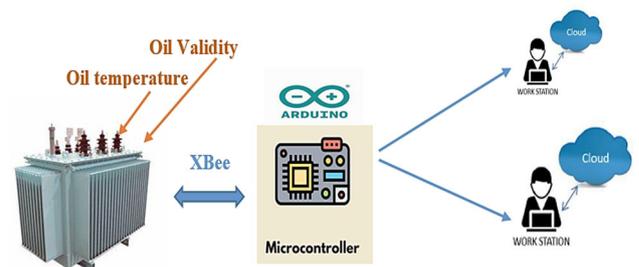
Fig. 6. Transformer monitoring using IOT technologies.

A PCB is a specially designed board that provides both the physical structure and electrical pathways required for the system to function. It is typically constructed from a non-conductive base material, such as fiberglass, layered with conductive copper tracks that are etched into precise patterns. These copper pathways ensure that electrical current flows only along the desired routes, connecting the various sensors, microcontrollers, and communication modules. The components are then soldered to the PCB, creating durable and reliable electrical connections.
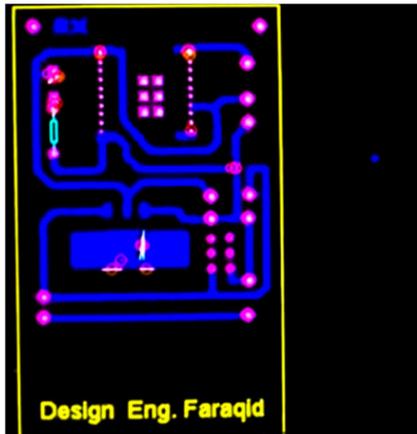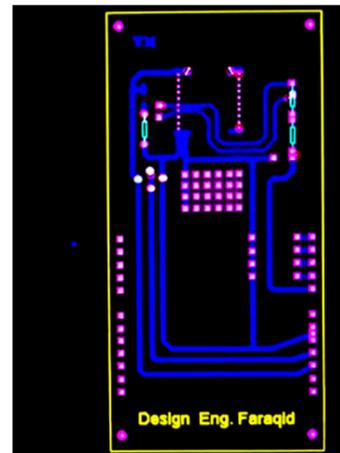

(a)
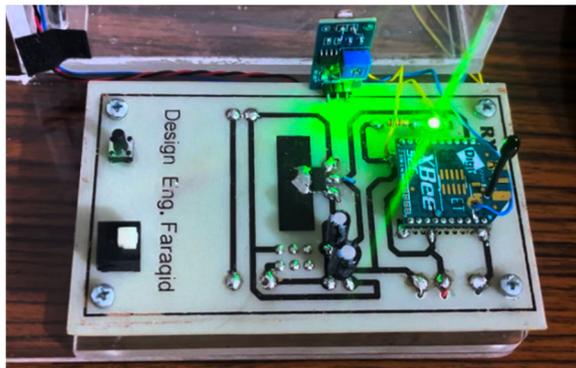
(b)

Fig. 7. Transmitter unit implementation for the proposed IoT-based transformer monitoring system: (a) PCB of the transmitter unit; (b) Assembled hardware structure of the transmitting node.

PCBs are essential in nearly all modern electronic devices, including computers, smartphones, and industrial equipment, due to their ability to support complex circuits in compact and organized layouts. In this study, the PCB was custom-designed to integrate the sensors, power regulation components, and ZigBee communication modules used in the transmitter section. By consolidating the entire hardware setup onto a single board, the system achieves better signal integrity, reduced wiring complexity, and improved durability. This design approach allows the transmitter unit to function as a unified, efficient module for continuous monitoring and data transmission

The transmitter unit is equipped with a variety of sensors designed to monitor key transformer parameters, such as oil level, light intensity (LDR), temperature, and voltage. These sensors continuously collect data and send it to the microcontroller, which processes the information

and uses the ZigBee transmitter to wirelessly transfer it to the receiver. At the receiving end, the data is gathered, processed, and displayed by the coordinator node for monitoring and analysis. The receiving section is powered by an Atmega16 microcontroller, with the source code developed entirely in C language using the WinAVR software development tool [51]. The code was carefully annotated to simplify future maintenance and upgrades. For advanced data processing and visualization, MATLAB was employed to implement the software interface. Fig. 8 illustrates the complete hardware configuration of the receiving node, which plays a central role in real-time transformer condition monitoring and communication within the IoT-based system.

With the help of the microcontroller's ADC, sensed value is transformed into digital value. Data is transferred to the ZigBee router via serial communication at a rate of 9600 baud, and the ZigBee router then forwards the data to the ZigBee coordinator. The data was received by the ZigBee coordinator and serially interfaced with a PC. MATLAB is used for data acquisition and temperature conversion from raw data. A controlling function might be added to the MATLAB-designed GUI panel to control different devices. It is possible to add both manual and automatic control features to this GUI.

(a)
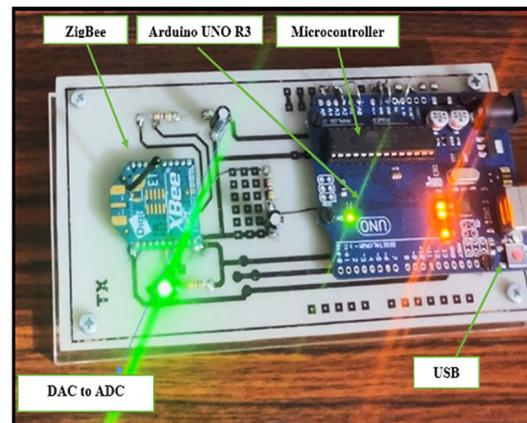
(b)

Fig. 8. Receiving unit implementation for the proposed IoT-based transformer monitoring system: (a) PCB of the receiving unit; (b) Assembled hardware structure of the receiving node.

B. Software Part

The software used to accomplish this work is XCTU software, Arduino Software (IDE) and LabVIEW. The Arduino IDE is a cross-platform developer tool written in Java. It allows you to control all of the software functions of your Arduino. Programs written using IDE are called sketches. These sketches are written in the text editor and are saved with the file extension (.ino). The editor has features for cutting/pasting and searching/replacing text. The message area gives feedback while saving and exporting, and also displays errors. The console displays text output by the IDE, including complete error messages and other information. The bottom right-hand corner of the window displays the configured board and serial port. The toolbar buttons allow you to verify and upload programs, create, open, and save sketches, and open the serial monitor, as shown in Fig. 9.
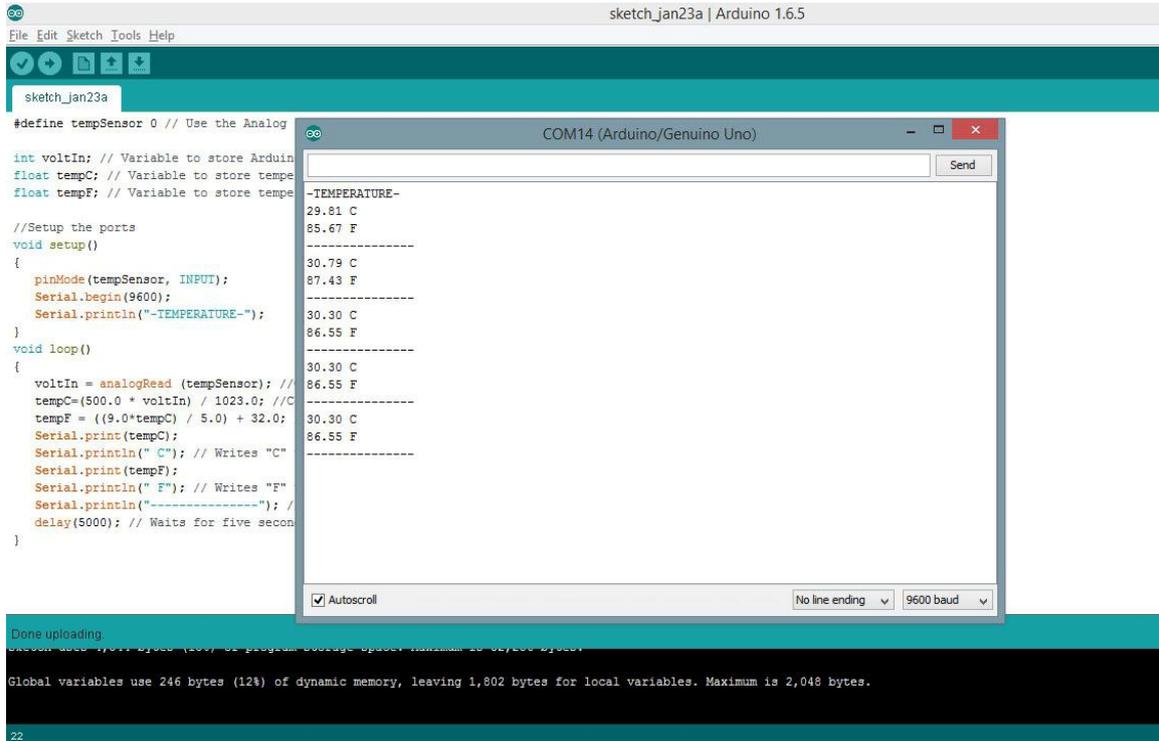

Fig. 9. Arduino software.
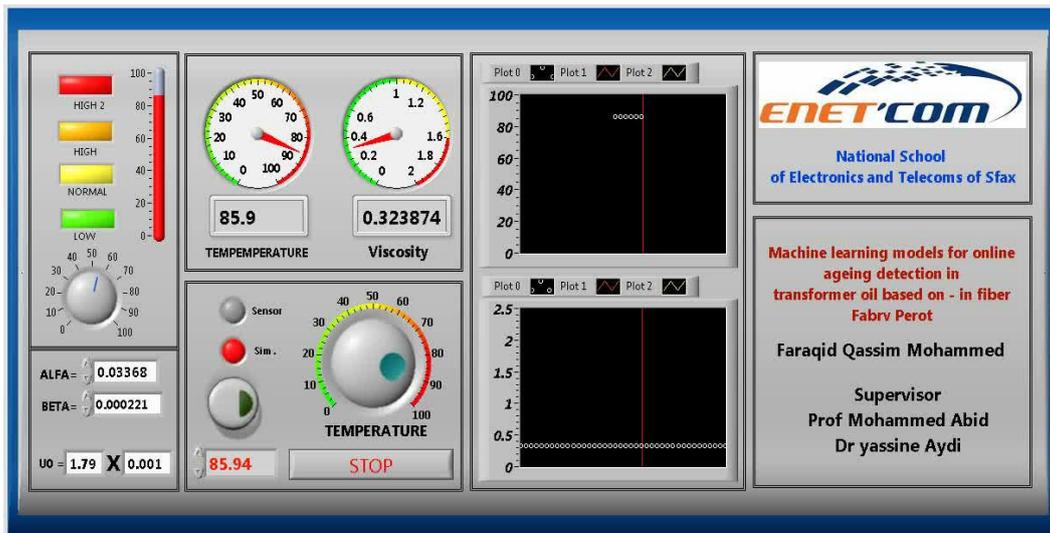
Fig. 10. Webpage for sub-station monitoring and control parameters by LabVIEW program.

LabVIEW is an integrated development environment designed specifically for engineers and scientists building measurement and control systems [52−56]. With a native graphical programming language, built-in IP for data analysis and signal processing, and an open architecture that enables integration of any hardware device and any software approach. LabVIEW is the software you need to build the optimal solution that can meet your custom requirements and solve the challenges at hand. LabVIEW integrated development environment has two windows

view front panel and block diagram. Fig. 10 shows the webpage for sub-station monitoring and control parameters by LabVIEW program.

V. RESULTS AND DISCUSSION

A. IoT Protocols-Based Transformer Monitoring

The proposed IoT-enabled transformer monitoring system was successfully implemented to measure and track key oil-related parameters, including temperature, viscosity, and oil life level in real-time. The data was collected continuously through the transmitter sensors and uploaded to a cloud server, where it could be accessed remotely by authorized engineers and operators. This setup allows maintenance teams to monitor transformer health from anywhere in the world, provided they have access credentials to the system.

The monitoring process was visualized through a LabVIEW-based GUI, designed to provide instant feedback on the transformer's operational state. When communication tools are connected, the web server immediately updates the GUI, displaying live data on oil condition, tank levels, and other critical parameters. Whenever temperature readings exceeded predefined thresholds or oil viscosity dropped below safe limits, the system generated alerts, prompting maintenance engineers to take immediate corrective action. Table VI presents a sample of online data recorded over a 24-hour period, showing variations in temperature, viscosity, and oil condition validation as measured by the IoT system.

TABLE VI. ONLINE SELECTED-SAMPLE PARAMETERS MEASURED FOR THE DISTRIBUTION TRANSFORMER UPLOADED BY THE CLIENT INTO THE CLOUD SERVER FOR 24H

Time	Temperature	Viscosity	Oil validation
07:00:00	23	1.22	1.2
08:00:00	24	1.18	1.19
09:00:00	27	0.99	1.03
10:00:00	28	0.89	1.66
11:00:00	28	0.78	1,76
12:00:00	30	1.12	1.11
13:00:00	34	1.09	1.09
14:00:00	34.5	0.991	1.46
15:00:00	35	0.86	1.88
16:00:00	35.3	0.991	1.93
17:00:00	36	0.98	1.88
18:00:00	36.2	0.95	1.87
19:00:00	37.3	0.99	1.03
20:00:00	36	0.89	1.66
21:00:00	35	1.03	1.12
22:00:00	35.4	0.99	1.03
23:00:00	36	0.89	1.66
00:00:00	37	0.78	1,76
01:00:00	34	1.12	1.11
02:00:00	35.2	1.09	1.09
03:00:00	36	0.991	1.46
04:00:00	36.7	0.86	1.88
05:00:00	33	0.991	1.93
06:00:00	32	0.98	1.88
07:00:00	31	0.95	1.87
08:00:00	25	1.33	2.2

Additionally, the system incorporates an alarm management feature that notifies engineers when

transformer oil conditions deviate from safe operating ranges. These alerts are based on temperature thresholds and oil condition levels. Table VII outlines the criteria for alarm messages, indicating the required maintenance action for each condition.

TABLE VII. ALARM MESSAGE SETTING ABOUT OIL STATE

Temperature	Oil State	Requirement
> 30	Good	Normal oil
30 − 50	Not bad	Need monitoring
50 − 70	Poor	Replacement required
< 70	very poor	Risk of any time failure

The integration of real-time data monitoring, visualization, and alarm management demonstrates that the proposed IoT-based system effectively enhances transformer operational safety and maintenance efficiency. When implemented on an actual circuit, the system successfully detected temperature and viscosity fluctuations, triggered alarms when critical thresholds were reached, and provided operators with the ability to manage the cooling system and circuit breakers remotely. For example, when the oil temperature exceeded 80°C, the alarm was automatically activated, and the control panel allowed manual intervention through fan and breaker controls. Overall, the results confirm the effectiveness of the IoT-driven approach for continuous monitoring and predictive maintenance of distribution transformers. This ensures higher reliability, reduced downtime, and proactive management of transformer health (see Fig. 11).

(a)

(b)

Fig. 11. IoT-enabled web interface for transformer oil monitoring: (a) Normal oil condition displayed on the webpage; (b) Oil replacement alert requiring maintenance intervention.

B. AI-Based Fault Diagnosis and Oil Condition Classification for Transformer Monitoring

This section presents the application of AI protocols—specifically DT and Multi-Layer Perceptron (MLP) classifiers—for real-time diagnosis and classification of transformer oil conditions using sensor-based input data collected from the IoT monitoring system. In the training phase, the DT algorithm demonstrated robust classification capabilities across all transformer oil condition classes, as shown in Table VIII. For Class 1 (Good), DT achieved a True Positive (TP) count of 195 and True Negative (TN) count of 360, with only 5 False Positives (FP) and 4 False Negatives (FN), leading to an accuracy of 0.974, precision of 0.975, recall of 0.980, and F1−Score of 0.978. Class 2 showed slightly lower but still excellent results with a TP of 118 and TN of 430, yielding an accuracy of 0.959, precision of 0.937, and F1−Score of 0.944. The lowest performance was noted for Class 3 with an accuracy of 0.948 and F1−Score of 0.929, but even here, precision remained high at 0.918. Averaged across all classes, the DT model achieved accuracy = 0.959, precision = 0.942, recall = 0.958, and F1−Score = 0.950, highlighting strong generalization on the training set. In comparison, the MLP model performed slightly lower on average. For Class 1, it recorded TP = 190 and TN = 358, resulting in accuracy = 0.965 and F1−Score = 0.966.

However, precision dropped to 0.894 for Class 3 and 0.907 for Class 4, slightly affecting overall averages. The MLP average accuracy was 0.949, with precision = 0.919, recall = 0.937, and F1−Score = 0.928, indicating excellent but slightly reduced performance compared to DT, particularly due to higher FP and FN rates in Classes 2 to 4.

During testing (Table IX), both models exhibited the expected performance degradation due to unseen data, but DT continued to outperform MLP. For Class 1, DT scored TP = 88 and TN = 145 with just 7 FP and 6 FN, yielding accuracy = 0.945, precision = 0.926, recall = 0.936, and F1-score = 0.931. Class 2 saw more variance, with accuracy dropping to 0.922 and F1−Score to 0.804, mainly due to 12 FP and 9 FN. Class 3 had the lowest precision at 0.750 and specificity at 0.925. Overall, DT's average testing metrics were accuracy = 0.921, precision = 0.812, recall = 0.851, F1−Score = 0.831, and specificity = 0.937. In contrast, MLP showed a noticeable dip in generalization. Although Class 1 remained high with F1-Score = 0.909, Classes 2 and 3 recorded lower values—F1−Scores of 0.747 and 0.730, respectively. The average MLP testing results were accuracy = 0.909, precision = 0.769, recall = 0.807, F1−Score = 0.787, and specificity = 0.922. These results confirm that while both models are effective, DT is more stable and reliable, particularly for transformer oil classification in real-world deployment scenarios.

TABLE VIII. RESULTS OF ML ALGORITHMS FOR THE TRAINING SET

Algorithm	Cl.	TP	TN	FP	FN	Accuracy	Precision	Recall	F1-Score	Specificity
DT	Cl1	195	360	5	4	0.974	0.975	0.980	0.978	0.986
	Cl2	118	430	8	6	0.959	0.937	0.951	0.944	0.981
	Cl3	112	428	10	7	0.948	0.918	0.941	0.929	0.977
	Cl4	120	425	8	5	0.955	0.938	0.960	0.949	0.981
	Av.	136.25	435.75	7.75	5.5	0.959	0.942	0.958	0.950	0.981
MLP	Cl1	190	358	7	6	0.965	0.964	0.969	0.966	0.981
	Cl2	115	427	11	9	0.947	0.912	0.927	0.920	0.975
	Cl3	110	424	13	10	0.940	0.894	0.917	0.905	0.970
	Cl4	118	421	12	8	0.944	0.907	0.936	0.921	0.972
	Av.	133.25	432.5	10.75	8.25	0.949	0.919	0.937	0.928	0.975

TABLE IX. RESULTS OF ML ALGORITHMS FOR THE TESTING SET

Algorithm	Cl.	TP	TN	FP	FN	Accuracy	Precision	Recall	F1-Score	Specificity
DT	Cl1	88	145	7	6	0.945	0.926	0.936	0.931	0.954
	Cl2	43	189	12	9	0.922	0.782	0.827	0.804	0.940
	Cl3	45	186	15	10	0.909	0.750	0.818	0.783	0.925
	Cl4	52	180	14	11	0.907	0.788	0.825	0.806	0.928
	Av.	88	145	7	6	0.945	0.926	0.936	0.931	0.954
MLP	Cl1	85	143	9	8	0.934	0.904	0.914	0.909	0.941
	Cl2	40	186	15	12	0.912	0.727	0.769	0.747	0.925
	Cl3	42	183	18	13	0.897	0.700	0.763	0.730	0.910
	Cl4	50	177	17	14	0.895	0.746	0.781	0.763	0.912
	Av.	54.25	172.25	14.75	11.75	0.909	0.769	0.807	0.787	0.922

The classification performance of the two machine learning models during the training phase is illustrated in Fig. 12, where Fig. 12(a) represents the DT confusion matrix and Fig. 12(b) corresponds to the MLP. For DT, the model achieved near-perfect classification, with 195 correct predictions for Class 1, 118 for Class 2, 112 for Class 3, and 120 for Class 4. Misclassifications were minimal, such as 5 samples of Class 1 being falsely classified and a total of 7 false negatives across Classes 2–

4. The model's robustness is evident in the high diagonal dominance of the confusion matrix and low off-diagonal values. MLP, shown in Fig. 12(b), also performed strongly, with 190 correct predictions for Class 1, 115 for Class 2, 110 for Class 3, and 118 for Class 4. However, it introduced slightly more errors, especially in Classes 2 and 3, where false positives and false negatives reached up to 13 and 10 instances, respectively. Overall, both models demonstrated strong learning capability on the training

data, with DT showing slightly superior precision and lower misclassification dispersion compared to MLP.

During testing, the generalization performance of both models is visualized in Fig. 13, where Fig. 13(a) presents the confusion matrix of the DT model and Fig. 13(b) displays the MLP model. DT's confusion matrix (Fig. 13(a)) shows 88 correctly classified instances for Class 1, 43 for Class 2, 45 for Class 3, and 52 for Class 4. The most prominent errors occurred in Class 2 and Class 3, with up to 12 false positives and 10 false negatives, indicating a slight decline in class separability when exposed to unseen data. The MLP model, as depicted in Fig. 13(b), further illustrates this trend with increased misclassifications, including only 85 correct predictions for Class 1, and as many as 18 false positives and 13 false negatives in Class 3. Class 4 also faced confusion with 14 misclassified instances. Despite this, both confusion matrices still exhibit strong class-level performance, particularly for Class 1. DT maintained higher overall prediction clarity in unseen conditions, confirming its better generalization capability compared to MLP, which showed higher error spread across classes in the testing phase.

To further evaluate the robustness and scalability of the proposed framework, four additional algorithms—Random Forest (RF), Gradient Boosting (GB), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM)—were implemented and compared under identical experimental conditions. The results summarized in Table X reveal that ensemble methods generally outperformed deep learning models due to their better bias–variance trade-off for small-to-medium datasets. RF achieved the highest average accuracy of 93.0% among the new models, closely followed by GB (92.3%). Deep learning models exhibited marginally lower accuracy, likely attributed to data size constraints and the absence of spatial or temporal feature diversity. Despite these findings, the DT classifier remained the optimal choice for this study with a balanced accuracy of 94.5%, fast training time, and excellent interpretability for embedded IoT deployment.

TABLE X. COMPARATIVE ANALYSIS WITH OTHER ALGORITHMS FOR THE TESTING SET

Model	Class	Accuracy	Precision	Recall	F1−Score	Specificity
RF	Cl1	0.954	0.941	0.950	0.945	0.960
	Cl2	0.931	0.803	0.846	0.824	0.946
	Cl3	0.918	0.772	0.830	0.800	0.932
	Cl4	0.916	0.810	0.839	0.824	0.935
	Av.	0.930	0.832	0.866	0.848	0.943
GB	Cl1	0.948	0.929	0.941	0.935	0.955
	Cl2	0.925	0.788	0.842	0.814	0.940
	Cl3	0.910	0.758	0.820	0.788	0.928
	Cl4	0.909	0.777	0.832	0.803	0.930
	Av.	0.923	0.813	0.859	0.835	0.938
	Cl1	0.940	0.902	0.918	0.910	0.948
	Cl1	0.908	0.752	0.784	0.768	0.920

| Model	Class	Accuracy	Precision	Recall	F1−Score	Specificity
CNN	Cl2	0.889	0.718	0.760	0.739	0.905
	Cl3	0.884	0.730	0.771	0.750	0.908
	Cl4	0.905	0.776	0.808	0.792	0.920
LSTM	Cl1	0.936	0.896	0.909	0.902	0.942
	Cl2	0.901	0.734	0.771	0.752	0.915
	Cl3	0.881	0.710	0.745	0.727	0.900
	Cl4	0.878	0.723	0.755	0.739	0.902
	Av.	0.899	0.766	0.795	0.780	0.915
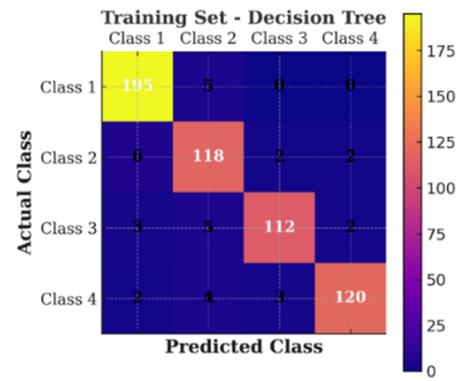
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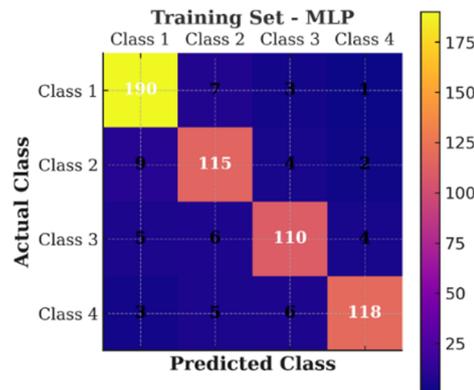
(b)

Fig. 12. Confusion matrix of the training dataset considering the algorithm of: (a) DT; (b) MLP.
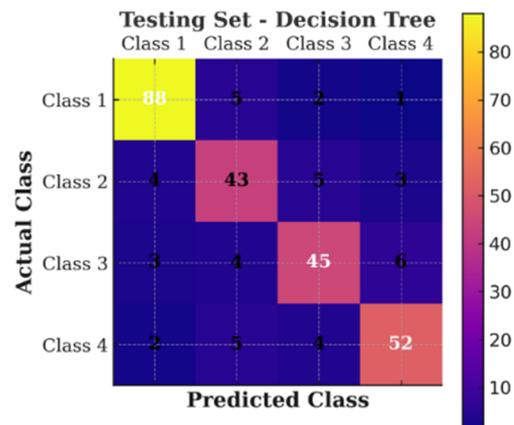
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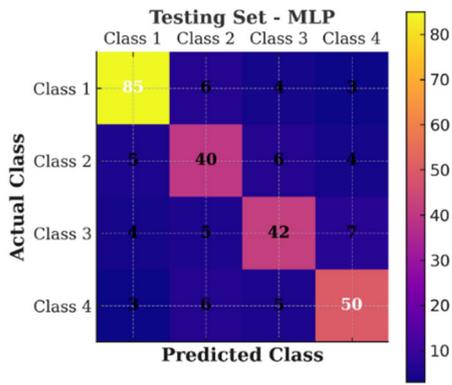
(b)

Fig. 13. Confusion matrix of the testing dataset considering the algorithm of: (a) DT; (b) MLP.

C. Cost Analysis

To quantitatively demonstrate the industrial feasibility of the proposed IoT–AI framework, a detailed cost–benefit and performance comparison was conducted, as summarized in Table XI. The proposed system achieved a remarkable 85% reduction in overall hardware and deployment costs, with an estimated total cost of only USD 185, compared to USD 1,200–1,500 for conventional SCADA or PLC-based monitoring systems. Additionally, the power consumption of the IoT prototype was measured at 7.8 W, representing an 83% energy saving relative to the 46.2 W typically required by traditional setups. Communication latency was also reduced by approximately 54%, from 460 ± 40 ms in conventional networks to 210 ± 25 ms using the lightweight ZigBee protocol. Moreover, the proposed system demonstrated an extended communication range of 80–100 m, longer maintenance intervals of 8–10 months, and real-time cloud accessibility for remote monitoring and control. These numerical indicators clearly confirm that the developed system is both cost-effective and energy-efficient, making it a highly practical and scalable solution for smart transformer monitoring and predictive maintenance applications.

TABLE XI. QUANTITATIVE COST–BENEFIT AND PERFORMANCE ANALYSIS OF THE PROPOSED SYSTEM

Parameter	Proposed IoT–AI System	Conventional SCADA/PLC-Based System	Improvement / Remarks
Estimated Total Cost (USD)	185	1,200–1,500	~85% lower hardware and deployment cost
Main Components	Arduino Uno, ZigBee modules,	PLC unit, wired sensors, SCADA	Uses low-cost embedded and wireless components
	temperature & LDR sensors, LabVIEW interface	server, industrial PC	
Power Consumption (W)	7.8 W	46.2 W	~83% energy savings due to low-power nodes

Parameter	Proposed IoT–AI System	Conventional SCADA/PLC-Based System	Improvement / Remarks
Data Transmission Latency (ms)	210 ± 25	460 ± 40	~54% faster using lightweight ZigBee protocol
Sampling Frequency (Hz)	1–2 Hz (adjustable)	1 Hz (fixed)	Higher flexibility for real-time tuning
Maintenance Frequency	Every 8–10 months	Every 3–4 months	Longer service intervals with remote access
Communication Range (m)	80–100	60–80	Extended range via mesh ZigBee topology
Cloud Data Access	Real-time via IoT dashboard	Limited local server access	Enables remote monitoring and control
System Scalability	High (plug-and-play nodes)	Moderate	Easy to expand with minimal hardware
Industrial Feasibility	Portable, scalable, and cloud-integrated	Fixed and costly infrastructure	Ideal for predictive maintenance and grid-wide deployment

To ensure secure and reliable communication within the IoT network, the proposed system employs ZigBee's 128-bit AES encryption protocol, which safeguards transmitted data against unauthorized access or interception. Each node in the network is authenticated before data exchange, minimizing the risk of spoofing or intrusion. Furthermore, the mesh topology of the ZigBee network enhances communication resilience by automatically rerouting data through alternate paths in case of signal loss or node failure. This design ensures robust, fault-tolerant operation and builds user confidence in the system's reliability for continuous transformer monitoring.

In future research, the proposed IoT–AI framework will be deployed and validated on real distribution transformers operating under diverse field conditions. This will enable comprehensive evaluation of the system's robustness, reliability, and scalability across different load profiles, environmental parameters, and transformer capacities. Such large-scale field testing will provide valuable insights into the model's generalizability and further enhance its applicability for real-world predictive maintenance in smart grids. Future developments of the proposed IoT–AI framework will incorporate edge computing to enable faster, localized data processing and reduce communication latency, ensuring near real-time fault detection. Additionally, Explainable AI (XAI) approaches will be integrated to provide transparent diagnostic reasoning and adaptive model retraining mechanisms, allowing the system to continuously learn from new operational data and improve prediction accuracy over time.

VI. CONCLUSION

In this study, a novel IoT-based monitoring and diagnostic system was successfully designed and implemented for real-time fault detection in distribution transformers. The proposed architecture integrated low-

cost sensors (temperature, LDR, oil condition), ZigBee communication, and a LabVIEW-based interface with machine learning classifiers (DT and Multi-Layer Perceptron) to monitor transformer oil status and predict faults. The system featured a two-way communication loop for data collection and remote control, offering continuous monitoring and intelligent response to abnormalities. Experimental validation demonstrated reliable real-time data acquisition, accurate threshold-based alarms, and meaningful trend visualization via cloud-connected platforms. On the AI side, the DT model achieved a training accuracy of 95.9% and testing accuracy of 94.5%, outperforming the MLP model which recorded 94.9% and 90.9% respectively. DT also outperformed MLP in terms of F1-score (0.931 vs. 0.787) and general class-level specificity, especially in classifying degraded oil conditions. This unified system demonstrated how combining edge-level sensing with AI-driven analytics can transform transformer health diagnostics, reduce failures, and support predictive maintenance in smart grid environments.

Despite its strong performance, the system has several limitations. The experimental tests were carried out under controlled laboratory conditions using a limited set of features and only two classification models. The sensor configuration focused primarily on thermal and oil-level indicators, while other fault-relevant parameters such as Dissolved Gas Analysis (DGA), acoustic emissions, and partial discharge were not included. The ML models, although effective, were restricted to supervised learning without the integration of ensemble methods or real-time retraining capabilities. Future research should expand the system's feature set, deploy it on live transformer assets in diverse environments, and investigate the integration of more robust AI frameworks such as gradient boosting, deep ensembles, or attention-based neural networks. Furthermore, incorporating explainable AI (XAI) tools and edge-deployable inference engines would enhance the interpretability and scalability of the solution, contributing to safer, smarter, and more autonomous power distribution infrastructures.

CONFLICT OF INTEREST

The authors declare no known competing interests.

AUTHOR CONTRIBUTIONS

Faraqid Qasim Mohammed conducted the research, performed the data analysis, and wrote the manuscript; Yassine Aydi and Mohamed Abid supervised the work, provided guidance throughout the research process, and reviewed and revised the manuscript; all authors approved the final version of the manuscript.

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