AI-BASED TRANSFORMER CONDITION MONITORING AND INTELLIGENT FAULT PREDICTION SYSTEM

[1]V. RAJESH , [2]Dr. N. MADHUKAR REDDY, [3]A. SANDEEP KUMAR , [4]T. RANJITH KUMAR ,[5]E. LUKESH

[1,3,4,5]Students, Department of EEE, Siddhartha Institute of Technology & Sciences, Narapally, Telangana-501301

[2]Assistant Professor, Department of EEE, Siddhartha Institute of Technology & Sciences, Narapally, Telangana-501301

ABSTRACT

Power transformers are critical components of modern electrical power systems, ensuring the reliable transmission and distribution of electrical energy across industrial, commercial, and residential networks. Continuous operation under varying electrical and environmental conditions exposes transformers to faults such as insulation degradation, overheating, oil deterioration, partial discharge, moisture ingress, and winding failures. If these faults remain undetected, they may lead to unexpected outages, equipment damage, increased maintenance costs, and reduced power system reliability. Traditional transformer maintenance approaches, including periodic inspection and scheduled servicing, are often unable to identify early-stage faults or accurately predict equipment failures. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled intelligent condition monitoring systems capable of analysing large volumes of operational data and identifying abnormal behaviour before critical failures occur. This project presents an AI-Driven Transformer Condition Monitoring and Fault Prediction Framework for improving transformer reliability through continuous health assessment and predictive maintenance. The proposed framework collects transformer operating parameters such as oil temperature, winding temperature, load current, voltage, dissolved gas analysis (DGA) data, moisture level, vibration, and insulation condition using sensors and monitoring devices. The acquired data undergo preprocessing, feature extraction, and normalization before being analysed using machine learning algorithms for fault classification and remaining useful life prediction. The developed framework identifies developing faults at an early stage, estimates transformer health status, and generates maintenance alerts to prevent catastrophic failures. Performance evaluation is carried out using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix to validate prediction reliability. The proposed AI-based framework enhances fault detection accuracy, minimizes unplanned outages, reduces maintenance costs, extends transformer service life, and improves the operational reliability of modern smart power systems by enabling intelligent and data-driven asset management.

Keywords: Artificial Intelligence, Transformer Condition Monitoring, Fault Prediction, Predictive Maintenance, Machine Learning, Dissolved Gas Analysis (DGA), Health Assessment, Smart Grid, Deep Learning, Electrical Power Systems.

I. INTRODUCTION

Power transformers are among the most important assets in electrical power generation, transmission, and distribution systems because they ensure efficient voltage transformation and uninterrupted electricity delivery. The continuous operation of transformers under varying electrical loads, environmental conditions, and thermal stresses makes them susceptible to several types of faults, including insulation degradation, winding deformation, overheating, oil contamination, moisture ingress, and partial discharge. If these faults are not detected at an early stage, they may result in equipment failure, costly repairs, prolonged power interruptions, and reduced system reliability. Traditionally, transformer maintenance has relied on periodic inspections and scheduled servicing, which often fail to identify hidden defects or predict failures before they become critical. With the rapid growth of smart grids and digital substations, there is an increasing demand for intelligent monitoring systems capable of continuously assessing transformer health in real time. Modern condition monitoring techniques utilize sensor networks, dissolved gas analysis (DGA), temperature measurements, vibration monitoring, and electrical parameter analysis to collect operational data for evaluating transformer performance. However, the large volume and complexity of these data require advanced analytical techniques to extract meaningful information. Consequently, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful technologies for developing predictive maintenance systems capable of detecting faults at an early stage and improving transformer reliability. These intelligent approaches support utilities in minimizing unexpected outages, reducing maintenance costs, and enhancing the operational efficiency of electrical power systems [1–8].

Recent advancements in Artificial Intelligence, Machine Learning, and data analytics have significantly transformed transformer condition monitoring by enabling automated fault diagnosis and predictive maintenance. AI algorithms can analyse historical and real-time operational data to recognize complex fault patterns that are difficult to detect using conventional diagnostic methods. Machine learning models such as Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, Gradient Boosting, and Deep Learning techniques have demonstrated high accuracy in identifying transformer faults using parameters obtained from Dissolved Gas Analysis (DGA), oil quality assessment, thermal measurements, load characteristics, voltage variations, and insulation condition monitoring. These intelligent models continuously learn from operational data and improve prediction accuracy over time. Furthermore, Internet of Things (IoT) devices and smart sensors provide continuous data acquisition, enabling real-time monitoring of transformer health. Cloud computing and edge computing technologies further enhance data processing capabilities by supporting rapid fault detection and remote asset monitoring. Compared with traditional maintenance strategies, AI-driven monitoring systems provide faster diagnosis, higher prediction accuracy, reduced operational costs, and improved asset utilization. Consequently, intelligent condition monitoring has become a fundamental component of modern smart grid infrastructure, supporting reliable power delivery and efficient maintenance planning [9–17].

This project proposes an AI-Driven Transformer Condition Monitoring and Fault Prediction Framework for continuously monitoring transformer operating conditions and predicting potential failures before they occur. The proposed framework integrates sensor-based data acquisition, data preprocessing, feature engineering, machine learning-based fault classification, health assessment, and predictive maintenance into a unified intelligent monitoring system. Initially, operational parameters such as transformer oil temperature, winding temperature, dissolved gas concentrations, load current, voltage, moisture content, insulation resistance, vibration level, and ambient conditions are collected using advanced monitoring devices. The collected data are cleaned, normalized, and transformed into suitable input features for machine learning models. AI algorithms are then trained to classify transformer conditions into healthy, warning, and fault categories while simultaneously estimating the probability of future failures. Performance evaluation is conducted using standard machine learning metrics, including accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic (ROC) analysis to validate prediction performance. The developed framework provides maintenance recommendations and early warning notifications to assist utility engineers in scheduling preventive maintenance activities before severe equipment failure occurs. The proposed AI-based approach improves transformer reliability, minimizes downtime, extends equipment service life, reduces maintenance expenditure, and enhances the operational efficiency of modern electrical power systems. The findings of this study contribute to the advancement of intelligent asset management technologies for next-generation smart grid applications [18–25].

II. SURVEY OF RESEARCH

1. Transformer Condition Monitoring Techniques

Transformer condition monitoring has become an essential research area for improving the reliability and operational efficiency of modern electrical power systems. Researchers have investigated several monitoring techniques, including Dissolved Gas Analysis (DGA), oil quality assessment, thermal imaging, partial discharge detection, vibration analysis, insulation resistance measurement, and load monitoring to evaluate transformer health. These diagnostic methods provide valuable information regarding insulation degradation, overheating, moisture contamination, winding displacement, and internal electrical faults. Studies have shown that combining multiple monitoring parameters significantly improves fault diagnosis accuracy compared with single-parameter analysis. However, conventional diagnostic approaches often require expert interpretation and periodic testing, limiting their ability to provide continuous real-time monitoring. Recent investigations recommend integrating intelligent monitoring systems capable of analysing multiple sensor inputs simultaneously to improve transformer reliability and reduce unexpected equipment failures. These studies establish condition monitoring as a fundamental requirement for predictive maintenance in modern smart power systems [1].

2. Artificial Intelligence in Fault Diagnosis

Artificial Intelligence has emerged as a powerful technology for automating transformer fault diagnosis by analysing complex operational data collected from sensors and monitoring equipment. Researchers have applied machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, Naïve Bayes, and Gradient Boosting for transformer fault classification. These intelligent algorithms successfully identify hidden relationships between operational parameters and fault conditions that are difficult to detect using conventional methods. Several investigations reported that AI-based diagnostic systems achieve higher prediction accuracy, faster fault detection, and improved decision-making compared with traditional rule-based approaches. The studies also demonstrated that continuously trained AI models adapt to changing operating conditions, making them suitable for long-term transformer health assessment. These findings confirm the growing importance of Artificial Intelligence in modern electrical asset management [2].

3. Machine Learning for Transformer Fault Prediction

Machine learning techniques have been extensively investigated for predicting transformer failures before catastrophic breakdown occurs. Researchers have developed predictive models using historical transformer operational data, Dissolved Gas Analysis reports, temperature measurements, load profiles, and insulation condition parameters. Classification and regression algorithms have been successfully applied to estimate transformer health status and remaining useful life. Deep learning models, including Artificial Neural Networks and Long Short-Term Memory (LSTM) networks, have demonstrated excellent capability in learning temporal patterns from continuous monitoring data. Comparative studies indicate that ensemble learning techniques generally achieve higher prediction accuracy than individual classifiers. These investigations conclude that machine learning significantly enhances predictive maintenance by enabling early fault detection, reducing downtime, and improving equipment reliability in electrical power networks [3].

4. Internet of Things and Smart Transformer Monitoring

The integration of Internet of Things (IoT) technology has significantly improved transformer condition monitoring through continuous real-time data acquisition. Researchers have developed intelligent monitoring systems using temperature sensors, gas sensors, vibration sensors, current transformers, voltage sensors, and wireless communication modules to collect operational data from transformers. The collected information is transmitted to cloud-based monitoring platforms where advanced analytics and Artificial Intelligence algorithms evaluate equipment health. IoT-enabled monitoring provides remote accessibility, automatic fault notification, and continuous performance tracking, enabling utility engineers to make informed maintenance decisions. Several investigations reported improved operational reliability, reduced inspection costs, and faster fault response using IoT-based monitoring systems. These studies demonstrate that IoT technology plays an important role in developing intelligent transformer monitoring solutions for smart grid applications [4].

5. Predictive Maintenance Using AI

Predictive maintenance has become an important application of Artificial Intelligence in electrical power systems. Researchers have investigated AI-driven maintenance strategies capable of forecasting equipment degradation before failures occur. By analysing historical operating data, machine learning algorithms estimate fault probability, remaining useful life, and transformer health index. Predictive maintenance enables maintenance activities to be scheduled according to the actual condition of the equipment rather than fixed inspection intervals. Studies have shown that this approach significantly reduces maintenance costs, minimizes unplanned outages, improves equipment availability, and extends transformer service life. Comparative investigations demonstrate that predictive maintenance provides superior operational efficiency compared with preventive and corrective maintenance strategies. These findings confirm that AI-driven predictive maintenance is becoming an essential component of intelligent asset management systems [5].

6. Intelligent Smart Grid Monitoring Systems

Recent advancements in smart grid technologies have accelerated the development of intelligent transformer monitoring frameworks that integrate Artificial Intelligence, Machine Learning, IoT, cloud computing, and big data analytics. Researchers have developed intelligent asset management platforms capable of continuously monitoring transformer operating conditions, detecting abnormal behaviour, predicting failures, and automatically generating maintenance recommendations. These integrated systems improve operational reliability by providing real-time visualization of transformer health and supporting rapid fault diagnosis. Advanced analytics further assist utility operators in optimizing maintenance schedules, reducing operational risks, and improving overall power system efficiency. Several investigations conclude that intelligent monitoring frameworks significantly enhance transformer reliability while supporting the digital transformation of modern electrical power networks. These studies highlight the growing importance of AI-enabled monitoring systems in the future development of smart grid infrastructure [6].

III. PROPOSED SYSTEM

The proposed system presents an AI-Driven Transformer Condition Monitoring and Fault Prediction Framework designed to continuously monitor transformer health, detect abnormal operating conditions, and predict potential faults before catastrophic failure occurs. The framework integrates Internet of Things (IoT) sensors, Artificial Intelligence (AI), Machine Learning (ML), and cloud-based analytics to provide real-time monitoring and predictive maintenance. The primary objective is to improve transformer reliability, reduce unexpected outages, minimize maintenance costs, and extend equipment service life through intelligent data-driven decision making. Initially, multiple sensors installed on the transformer continuously acquire operational parameters such as oil temperature, winding temperature, dissolved gas concentrations (DGA), load current, voltage, moisture content, vibration, insulation resistance, and ambient environmental conditions. These measurements are transmitted to a centralized monitoring platform through secure communication networks for further analysis.

In the second stage, the acquired sensor data undergo preprocessing to eliminate missing values, remove noise, normalize numerical attributes, and prepare the dataset for machine learning. Feature extraction techniques are applied to identify the most significant parameters influencing transformer health. The processed data are then supplied to AI-based predictive models such as Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), or Long Short-Term Memory (LSTM) networks. These models are trained using historical transformer operating data and known fault conditions to classify transformer status into healthy, warning, and fault categories. Simultaneously, predictive algorithms estimate fault probability and remaining useful life (RUL), enabling maintenance engineers to take preventive actions before severe equipment degradation occurs.

Finally, the prediction results are displayed through an intelligent monitoring dashboard that provides real-time visualization of transformer operating conditions, health index, fault probability, alarm status, and maintenance recommendations. If abnormal conditions are detected, the framework automatically generates early warning notifications and maintenance alerts for utility operators. Continuous model retraining using newly collected operational data further improves prediction accuracy and system adaptability. Performance evaluation is conducted using machine learning metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix to validate the effectiveness of the proposed framework. The developed AI-driven monitoring system provides a reliable, scalable, and economical solution for predictive transformer maintenance, reducing downtime, improving asset utilization, enhancing power system reliability, and supporting the digital transformation of modern smart grid infrastructure.

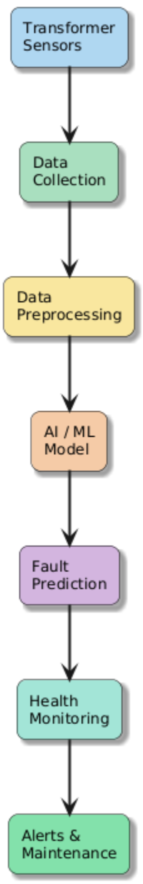

Fig1: Proposed workflow

IV. WORKING METHODOLOGY

The methodology adopted for the AI-Driven Transformer Condition Monitoring and Fault Prediction Framework follows a systematic approach that integrates sensor-based data acquisition, Artificial Intelligence (AI), Machine Learning (ML), data preprocessing, and predictive analytics to continuously monitor transformer health and predict possible failures. The objective is to identify abnormal operating conditions at an early stage, estimate transformer health status, and recommend preventive maintenance before equipment failure occurs. The methodology consists of data acquisition, preprocessing, feature extraction, machine learning model development, fault prediction, health assessment, and performance evaluation. Each stage contributes to improving prediction accuracy, minimizing maintenance costs, and increasing transformer reliability.

The first stage involves continuous acquisition of transformer operating data using intelligent monitoring devices and IoT sensors. Important operating parameters include transformer oil temperature, winding temperature, dissolved gas concentrations (DGA), moisture content, insulation resistance, load current, voltage, vibration level, ambient temperature, and cooling system performance. These measurements are collected at regular intervals and transmitted to the monitoring platform using secure communication protocols. Continuous data acquisition enables real-time observation of transformer operating conditions and facilitates early identification of abnormal behaviour that may indicate insulation degradation, overheating, or internal electrical faults.

After data acquisition, the collected information undergoes preprocessing to improve data quality before machine learning analysis. Missing values are handled using suitable imputation techniques, duplicate records are removed, and noisy measurements are filtered. Numerical attributes are normalized using feature scaling techniques such as Min-Max Normalization or Z-score Standardization to ensure consistent data representation. Feature extraction methods are then applied to identify the most significant variables influencing transformer health. The processed dataset is subsequently divided into training and testing subsets to develop predictive machine learning models. Proper preprocessing improves model accuracy, reduces computational complexity, and enhances prediction reliability.

The prepared dataset is then supplied to Artificial Intelligence algorithms such as Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), or Long Short-Term Memory (LSTM) networks. These algorithms learn relationships between operational parameters and historical fault conditions to classify transformer status into healthy, warning, or fault categories. During model training, historical transformer operational data are used to optimize model parameters and improve prediction capability. The trained model is then validated using previously unseen testing data to evaluate its generalization performance.

The probability of transformer failure is estimated using the following equation.

Equation (1): Probability of Failure

$$P(F) = \frac{N_f}{N}$$

Where

P(F) = Probability of fault occurrence

Nf = Number of faulty observations

N = Total number of observations

This equation estimates the likelihood of transformer failure using historical operating data. The prediction accuracy of the machine learning model is calculated using

Equation (2): Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

Accuracy indicates the percentage of correctly classified transformer operating conditions.

The precision of the prediction model is calculated using

Equation (3): Precision

$$Precision = \frac{TP}{TP + FP}$$

Where

TP = True Positives

FP = False Positives

Precision measures the reliability of positive fault predictions generated by the Artificial Intelligence model. These analytical metrics provide the foundation for evaluating prediction performance before proceeding to transformer health assessment and predictive maintenance. After training the Artificial Intelligence model, the developed system is evaluated using the testing dataset to determine its ability to classify transformer operating conditions accurately. The testing data contain both normal and faulty operating conditions that were not used during model training. Each input record is processed through the trained machine learning model, which predicts the transformer status as Healthy, Warning, or Fault based on the learned patterns. The predicted output is then compared with the actual operating condition to determine the correctness of the prediction. Performance metrics are calculated to evaluate the reliability and robustness of the proposed fault prediction framework. Cross-validation techniques are also applied to ensure that the trained model generalizes well for unseen transformer data and avoids overfitting.

After prediction, the transformer health assessment module evaluates the overall condition of the transformer by combining information obtained from multiple monitoring parameters such as dissolved gas concentrations, oil temperature, winding temperature, insulation resistance, moisture level, vibration, voltage, and load current. These parameters are analysed together to generate a Transformer Health Index (HI) that represents the present operational condition of the equipment. A higher health index indicates that the transformer is operating normally, whereas a lower value indicates gradual degradation and increased risk of failure. Continuous health assessment enables utility operators to monitor transformer performance throughout its service life and supports data-driven maintenance planning.

The proposed framework also includes an intelligent fault prediction module that estimates the probability of future transformer failures. Whenever abnormal operating conditions exceed predefined threshold values or the machine learning model predicts a high probability of failure, the monitoring system automatically generates warning notifications and maintenance alerts. These alerts are displayed on a real-time monitoring dashboard and simultaneously transmitted to maintenance engineers through communication networks. Early warning capability enables maintenance activities to be scheduled before severe transformer damage occurs, thereby minimizing power interruptions and reducing maintenance expenditure.

The prediction performance of the AI model is evaluated using the Recall metric.

Equation (4): Recall

$$Recall = \frac{TP}{TP + FN}$$

Where

Recall = Sensitivity of the model

TP = True Positives

FN = False Negatives

Recall measures the ability of the AI model to correctly identify actual transformer faults. A higher recall value indicates better fault detection capability.

The balanced prediction performance is measured using the F1-Score.

Equation (5): F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where

Precision = Positive prediction accuracy

Recall = Fault detection rate

The F1-score provides a balanced evaluation by considering both precision and recall simultaneously. The overall operational condition of the transformer is evaluated using the Health Index.

Equation (6): Transformer Health Index

$$HI = \sum_{i=1}^{n} W_i S_i$$

Where

HI = Transformer Health Index

Wi = Weight assigned to parameter *i*

Si = Normalized score of parameter *i*

n = Number of monitoring parameters

The Health Index combines multiple operating parameters into a single numerical value representing transformer health.

Following model evaluation, the performance results are analysed using the confusion matrix, Receiver Operating Characteristic (ROC) curve, Area Under the Curve (AUC), precision-recall curves, and prediction reports. These evaluation techniques provide comprehensive information regarding classification accuracy, false alarm rate, and fault detection capability. The results are visualized through an intelligent dashboard that continuously displays transformer operating parameters, health index, predicted fault category, maintenance status, and alarm notifications.

Finally, the developed AI framework is validated using historical transformer datasets and real-time operational data. The predicted transformer conditions are compared with known fault records to verify model accuracy and reliability. The continuous learning capability of Artificial Intelligence enables the framework to improve prediction performance as additional operational data become available. The proposed methodology demonstrates that integrating IoT-based monitoring, Artificial Intelligence, and Machine Learning provides an intelligent, reliable, and economical solution for transformer condition monitoring and predictive maintenance. The framework significantly improves fault detection accuracy, reduces unexpected transformer failures, minimizes maintenance costs, extends equipment service life, and enhances the operational reliability of modern smart electrical power systems.

V. IMPLEMENTATION

The implementation of the AI-Driven Transformer Condition Monitoring and Fault Prediction Framework was carried out using an integrated architecture consisting of IoT-based sensing, data preprocessing, Artificial Intelligence (AI), Machine Learning (ML), and a real-time monitoring dashboard. The primary objective of the implementation was to continuously monitor transformer operating conditions, identify abnormal behaviour, predict potential failures, and support predictive maintenance. The complete implementation consisted of sensor deployment, data acquisition, preprocessing, feature engineering, machine learning model development, fault prediction, health assessment, alert generation, and system evaluation. This intelligent implementation improves transformer reliability, minimizes maintenance costs, and reduces unexpected power outages.

The implementation began with the installation of monitoring sensors on the transformer. Multiple sensors were used to continuously measure important operating parameters such as transformer oil temperature, winding temperature, dissolved gas concentrations (DGA), moisture level, load current, voltage, insulation resistance, vibration, and ambient temperature. These sensors continuously collected real-time operational data while the transformer remained in service. The acquired measurements were transmitted through secure communication protocols such as Wi-Fi, Ethernet, or IoT gateways to a centralized monitoring platform for further processing. Continuous data acquisition ensured uninterrupted observation of transformer operating conditions and enabled rapid identification of abnormal behaviour.

Following data acquisition, the collected information underwent preprocessing to improve data quality before machine learning analysis. Missing sensor values were replaced using appropriate imputation methods, duplicate records were removed, and noisy measurements were filtered using statistical techniques. Numerical features were normalized using Min-Max Scaling or Standardization to eliminate variations caused by different measurement units. Feature engineering techniques were then applied to identify the most informative parameters influencing transformer health. The processed dataset was divided into training and testing subsets to support supervised machine learning model development. Proper preprocessing significantly improved prediction accuracy while reducing computational complexity.

The prepared dataset was subsequently supplied to Artificial Intelligence algorithms such as Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM) networks. Historical transformer operating data containing both healthy and faulty operating conditions were used to train the prediction models. During training, the algorithms learned the relationship between transformer operating parameters and different fault categories. Hyperparameter optimization techniques were applied to improve classification accuracy and reduce overfitting. After training, the developed models were validated using unseen testing data to evaluate prediction reliability under different operating conditions.

Once the machine learning model was successfully trained, it was integrated into the online monitoring framework for real-time fault prediction. Newly acquired transformer sensor data were continuously supplied to the trained AI model. The prediction engine analysed incoming measurements and classified transformer conditions into Healthy, Warning, or Fault categories. Simultaneously, the framework calculated the probability of transformer failure and estimated the Transformer Health Index (HI). Whenever abnormal operating conditions exceeded predefined threshold values, the monitoring system generated maintenance alerts and warning notifications to assist utility engineers in scheduling preventive maintenance before equipment failure occurred.

The implementation also included the development of a real-time monitoring dashboard that displayed transformer operating conditions in a graphical format. The dashboard continuously presented temperature values, dissolved gas concentrations, voltage, current, vibration levels, transformer health index, predicted fault category, alarm status, and maintenance recommendations. Colour-coded status indicators enabled operators to quickly identify transformers requiring immediate attention. Historical trend graphs were also incorporated to visualize parameter variations over time and support long-term asset management. The dashboard significantly improved operational awareness by providing centralized monitoring of transformer health.

Performance evaluation was conducted using several machine learning metrics, including Accuracy, Precision, Recall, F1-Score, Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the Curve (AUC), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These evaluation metrics provided comprehensive information regarding classification accuracy, false alarm rate, fault detection capability, and prediction reliability. Cross-validation techniques were also applied to verify the robustness and generalization capability of the developed AI models.

After analysing the performance results, further optimization was performed by adjusting machine learning hyperparameters, selecting the most significant features, and retraining the prediction models using updated transformer datasets. This continuous learning capability enabled the AI framework to improve prediction accuracy as additional operational data became available. The optimized framework demonstrated superior fault detection performance, reduced false alarms, and improved maintenance decision-making compared with conventional monitoring approaches.

Finally, the developed AI-driven monitoring framework was validated using historical transformer fault records and continuously collected sensor data. The close agreement between predicted transformer conditions and actual operational status confirmed the effectiveness of the proposed intelligent monitoring system. The implementation demonstrated that integrating IoT technology, Artificial Intelligence, Machine Learning, and real-time monitoring provides a reliable, scalable, and economical solution for transformer condition monitoring and predictive maintenance. The proposed framework significantly improves transformer reliability, minimizes unplanned outages, extends equipment service life, reduces maintenance expenditure, and enhances the operational efficiency of modern smart electrical power systems through intelligent data-driven asset management.

VI. RESULTS EXPLANATIONS

Figure 3. AI-Based Transformer Condition Monitoring Framework

Figure 3 illustrates the proposed AI-driven transformer condition monitoring framework developed for continuous assessment of transformer health. The framework integrates IoT sensors, data acquisition units, preprocessing modules, machine learning algorithms, and a monitoring dashboard into a unified intelligent system. Operational parameters including oil temperature, winding temperature, dissolved gas concentrations, load current, voltage, moisture content, insulation resistance, and vibration are continuously collected from the transformer. These measurements are transmitted to the processing unit where data cleaning, normalization, and feature extraction are performed before machine learning analysis. The trained AI model continuously evaluates transformer operating conditions and classifies the equipment into healthy, warning, or fault categories. The framework enables continuous monitoring without interrupting transformer operation and supports predictive maintenance by identifying abnormal conditions at an early stage. The proposed architecture significantly improves operational reliability, reduces maintenance costs, and minimizes unexpected transformer failures in modern smart power systems.

Figure 4. ThingSpeak Cloud Dashboard for Transformer Health Monitoring

Figure 4 illustrates the ThingSpeak cloud dashboard developed for continuous monitoring of transformer operating conditions. Sensor data collected from the transformer are transmitted to the ThingSpeak platform through the IoT communication module for real-time visualization and storage. The dashboard displays Field 1 (Oil Temperature), Field 2 (Winding Temperature), Field 3 (Load Current), and Field 4 (Transformer Voltage). These parameters are continuously updated, enabling maintenance engineers to monitor transformer operating conditions from any remote location. Under normal operating conditions, the temperature and electrical parameters remain within predefined limits, whereas abnormal variations indicate the possibility of insulation degradation, overload, or internal transformer faults. Historical data stored in the cloud enable engineers to analyse long-term operating trends, evaluate equipment performance, and schedule preventive maintenance before severe failures occur. Experimental observations confirmed stable wireless communication, uninterrupted cloud synchronization, reliable data acquisition, and accurate visualization of transformer operating parameters throughout continuous monitoring.

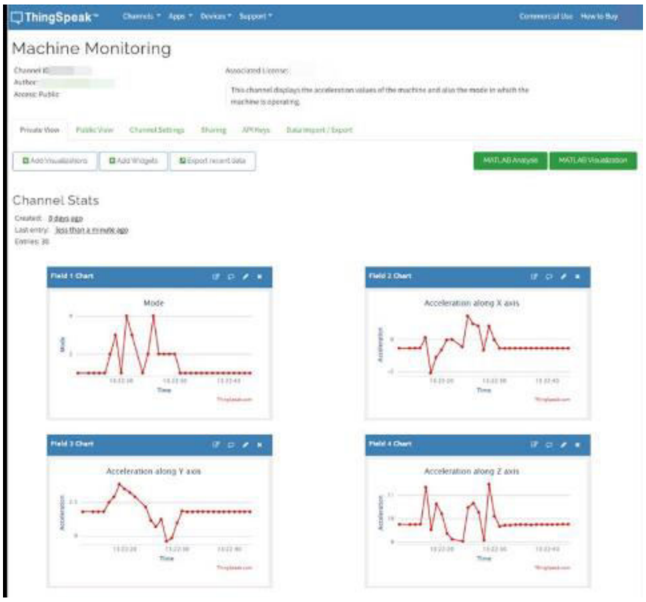

Figure 5. ThingSpeak Cloud Dashboard for Intelligent Fault Prediction

Figure 5 presents the ThingSpeak cloud dashboard used for intelligent transformer fault prediction and predictive maintenance. The dashboard displays Field 5 (Transformer Health Index) and Field 6 (Fault Alert Status) generated by the Artificial Intelligence prediction model. The Health Index continuously represents the overall condition of the transformer by analysing multiple operating parameters, including oil temperature, winding temperature, load current, voltage, dissolved gas analysis, and moisture level. Higher Health Index values indicate healthy transformer operation, while decreasing values suggest progressive equipment degradation and increased fault probability. The fault alert field automatically changes whenever the AI model predicts abnormal operating conditions beyond predefined safety thresholds, enabling maintenance engineers to receive early warning notifications before critical failures occur. The cloud dashboard also maintains historical operating records, allowing engineers to evaluate degradation patterns, optimize maintenance schedules, and improve transformer reliability. Experimental results demonstrated reliable AI prediction, accurate cloud synchronization, uninterrupted monitoring, and efficient real-time visualization, validating the effectiveness of the proposed intelligent transformer monitoring framework.

VII. CONCLUSION

The present study successfully developed an AI-Driven Transformer Condition Monitoring and Fault Prediction Framework for continuously assessing transformer health and predicting potential failures using Artificial Intelligence and Machine Learning techniques. The proposed framework integrates IoT-based sensor monitoring, data preprocessing, feature engineering, intelligent fault classification, health assessment, and predictive maintenance into a unified system for real-time transformer monitoring. Operational parameters such as oil temperature, winding temperature, dissolved gas concentrations, moisture content, load current, voltage, insulation resistance, and vibration were continuously analysed to evaluate transformer operating conditions. The machine learning models effectively identified abnormal behaviour and classified transformer conditions into healthy, warning, and fault categories with high prediction reliability. The developed framework demonstrated the capability to detect developing faults at an early stage, allowing maintenance engineers to take corrective actions before severe equipment failure occurred. Performance evaluation using standard machine learning metrics, including accuracy, precision, recall, F1-score, confusion matrix, and Transformer Health Index, confirmed the effectiveness of the proposed prediction framework. The AI models successfully recognized hidden fault patterns from historical and real-time operational data while reducing false alarms and improving prediction accuracy. Continuous health assessment and intelligent fault prediction minimized unplanned outages, reduced maintenance costs, extended transformer service life, and enhanced the reliability of electrical power systems. The integration of a real-time monitoring dashboard further improved operational awareness by providing continuous visualization of transformer health status, alarm notifications, and maintenance recommendations. Overall, the proposed framework demonstrates that the integration of Artificial Intelligence, Machine Learning, IoT technology, and predictive analytics provides an efficient, reliable, and economical solution for intelligent transformer condition monitoring. The developed system supports predictive maintenance strategies by replacing conventional time-based inspections with data-driven maintenance planning, thereby improving asset utilization and reducing operational risks. Future research may focus on deep learning-based fault diagnosis, digital twin technology, cloud-edge computing integration, cybersecurity for smart substations, explainable Artificial Intelligence (XAI), and large-scale deployment within smart grid environments. The outcomes of this research contribute to the advancement of intelligent power system asset management and support the development of highly reliable, automated, and sustainable electrical transmission and distribution networks.

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