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RESEARCH

Predictive Maintenance Optimization in Zigbee-Enabled Smart Home Networks: A Machine Learning-Driven Approach Utilizing Fault Prediction Models

Franciskus Antonius Alijoyo[1,2] · Rahul Pradhan[3] · N. Nalini[4] · Shaik Shakeel Ahamad[5] · Vuda Sreenivasa Rao[6] · Sanjiv Rao Godla[7]

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Abstract
The present research proposes a new machine learning-driven method that uses failure prediction models to address the critical need for reliable service scheduling beyond Zigbee-enabled smart home networks. The intention of employing predictive maintenance approaches and advanced analytics is to decrease costs and delay periods associated with equipment breakdowns. Smart home networks rely more on legitimate maintenance methods to control and run IoT devices, enhancing convenience and energy economy. The suggested methodology enables proactive upkeep by detecting system faults using modern machine learning techniques such as Firefly Optimization and XGBoost. Within the smart house network, data is collected from sensors and monitoring equipment and pre-processed to extract useful information for fault prediction. The XGBoost technique improves prediction accuracy by identifying hidden correlations in records. The algorithms are skilled in using historical records to hit upon traits that suggest probable faults or disasters in Zigbee-enabled devices. By combining XGBoost as well as Firefly Optimization into fault identification algorithms, this approach attempts to give well-timed and accurate forecasts, taking into consideration faster repairs and retaining the serviceability and dependability of clever home equipment. This approach differs because it employs exceptional machine learning algorithms, preprocessing of data, and hyperparameter changes to provide regular upkeep, hence extending the lifespan and reliability of smart home devices. The proposed framework is developed by python. The performance evaluation of the suggested models indicates their efficacy, having an accuracy score of 98%, highlighting their ability to address anticipates about servicing devices in Zigbee-enabled smart homes.

Keywords Fault prediction · Firefly optimization · Machine learning · Smart home · XGBoost · Zigbee

Extended author information available on the last page of the article

1 Introduction

The possibility of a "Smart home" has lighted a huge turmoil nowadays, because of its unparalleled solace, viability, and organization. At the forefront of this innovation are smart home networks—advanced ecosystems of interconnected devices and systems that automate and enhance various aspects of everyday life at home. These networks provide convenience in connected living and have completely transformed the way people communicate within their homes. From voice-activated assistants and security cameras to intelligent lighting controls and temperature regulation, smart home networks have revolutionized people's lifestyles [1].Current systems administration innovations empower areas of strength for connected gadgets and sensors that structure the premise of any smart home organization. Among the most famous conventions used to make smooth correspondence between gadgets inside the organization are Wi-Fi, Bluetooth, Zigbee, and Z-Wave. Using these conventions, electronic gadgets can impart, get orders, and plan activities together to frame a durable environment that fulfils occupants' necessities and inclinations [2]. One of the primary objectives of an intelligent home network is to increase customer comfort and convenience through automated household chores and user-friendly management of multiple home equipment. For instance, high-level sensor-prepared keen warmers can recognize inheritance drifts and change temperature settings properly, amplifying energy effectiveness and ensuring ideal solace levels. Similarly, ecological circumstances might be identified by brilliant lighting frameworks, which give programmable lighting plans to accomplish the expected climate while saving energy. In smart home networks, voice-activated assistants like Google Assistant and Amazon Alexa act as the primary command centres, allowing users to control a variety of services and appliances with simple voice commands. Voice assistants remove the need for complicated dashboards or manual manipulation and allow consumers to connect with their homes naturally and intuitively. Instances of these connections incorporate changing the temperature, darkening the lights, playing music, and submitting staple requests. Smart home networks also significantly contribute to increased safety and security because they incorporate cutting-edge monitoring and surveillance technologies. Occupants could follow their homes from a distance and make a move quickly in case of a security peril by utilizing intelligent cameras that are fitted with two sensors for development and evening noticing capacities. These cameras may broadcast live video transmissions and warnings. Intelligent locking instruments and entry components likewise give further developed admittance control, permitting property holders to give or drop admittance to their homes, expanding security and solace from a distance [3].

Additionally, digital carbon monoxide monitors and fire detectors may be able to identify potential threats and promptly notify homes, thereby lowering risks and decreasing the likelihood of mishaps. In the event of a crisis, these arranged safety efforts may likewise set off computerized responses that ensure the occupants' security, for example, turning on crisis lights or opening ways to empower escape. The two main advantages of smart home networks are their scalability and adaptability, which allow homeowners to modify and expand their systems in response to shifting requirements and preferences. Because of its secluded plan and viable principles, brilliant home organizations give unequalled adaptability to refreshing obsolete parts, presenting new gadgets, and coordinating external administrations. Due to their flexibility, brilliant homes should be fit for changing with the times and keep on being viable and significant for a long time to come [4]. Prescient support improvement's fuse into the quickly creating field of brilliant home innovation can change the upkeep and oversee residing spaces. In such a manner, Zigbee-empowered smart home frameworks become a fundamental stage, giving areas of strength for connecting different gadgets and sensors to permit precaution-support plans. Prescient upkeep streamlining builds the sturdiness and reliability of home frameworks and advances a more viable and efficient strategy for home administration by using data examination, AI procedures, too remote correspondence conventions like Zigbee. With the improvement of manmade reasoning, sensor innovation, and systems administration throughout recent years, the possibility of the "smart home" has taken various structures. A growing number of homes are being outfitted with a variety of networked appliances and systems that are intended to increase comfort, automate chores, and use less energy—things that just a few years ago seemed like they would only come into use in the future [5]. The idea of arranged knowledge, where devices effectively associate with coordinated activities and respond to human inclinations, is principal to the development of shrewd home environments. Because of its low energy utilization, expanded battery duration, and limit concerning monstrous organizations of gadgets, Zigbee, a lower-power remote correspondence convention, is presently a well-known choice for intelligent home systems administration. The underpinning of contemporary shrewd home organizations is comprised of Zigbee-empowered gadgets, which might be anything from entryway locks and movement indicators to indoor regulators and lighting controls. This makes it possible to work together and be compatible with a wide range of product categories. With smart home technology, there is no control or convenience like there has ever been before, but there are also special issues with maintenance and upkeep. As the number of connected devices in a household grows, it becomes more difficult to guarantee these electronics' dependability and effectiveness. Traditional methods of maintenance, which typically consist of reactive repairs and planned inspections, are frequently insufficient due to the constantly evolving and networked design of smart home devices [6].

Moreover, the expense and burden related to startling gadget disappointments or breakdowns could unidentify the general incentive of shrewd home advancements. In this setting, proactive maintenance solutions that use immediate form information and predictive analysis to find and avoid potential issues before they happen are becoming increasingly important. Predictive maintenance optimization has fundamentally altered how people maintain and manage smart home devices. Prescient upkeep, in its least difficult structure, conjectures potential breakdowns or execution crumbling using progressing gadget usefulness and execution measurements checking joined with refined scientific methodologies. Prescient upkeep permits homes to limit interference and burden by finding early advance notice signals and patterns signs of coming worries. This makes it possible for homeowners to take preventative measures like replacing or fixing equipment before it breaks down [7]. Predictive maintenance management provides information about the system's behaviour and performance by utilizing the vast amount of data generated by integrated Zigbee-enabled intelligent home devices. The data may be assessed to track down patterns, irregularities, and examples that can highlight forthcoming disappointments or terrible showings utilizing AI strategies and factual procedures. Predictive maintenance management is dependent on many essential components in Zigbee-enabled intelligent home networks to ensure the longevity and effective operation of networked systems and devices. Information assortment and observing, which incorporate social affair suitable data from connected gadgets and sensors inside the brilliant home organization, are the major parts of this system. That information includes continuous monitoring of the device's temperature, humidity, energy consumption, and operating state. Following the securing of the information, AI strategies and other complex examination approaches are utilized to track down examples and bits of knowledge in the information. Prescient models might be made to assess future support prerequisites by assessing past information and contrasting it and gadget execution. This permits mortgage holders to anticipate potential issues and make a move before they become more serious. Shortcoming findings and identification is a fundamental piece of precautionary support advancement. This includes distinguishing and diagnosing issues or irregularities in frameworks for smart homes prior in.

Through reliable perception of take-offs from expected direct and effectiveness benchmarks, any issues can be perceived and revealed for extra assessment, empowering property holders to pick preplanned activities to decrease risks and keep away from framework glitches [8]. Outfitted with bits of knowledge assembled through prescient demonstrating, mortgage holders might make proactive support timetables to handle recognized issues before they deteriorate into critical breakdowns. Planning preventative maintenance procedures like software upgrades, recalibration, or component replacement may be necessary to maximize system durability and efficiency. Utilizing these essential components, predictive maintenance management ensures the dependability, effectiveness, and viability of Zigbee-enabled intelligent home systems, allowing homeowners to maximize their smart home technology investments [9]. To discover patterns and correlations between input characteristics and target labels, effective machine-learning techniques derived from historical data include regression models and neural networks. Model decision and learning include picking these models. After preparing, the models are utilized to expect deserts and recognize abnormalities, using take-offs from average working conditions to detect any blunders or glitches. Autoencoders and isolation forests, for example, aid in the identification of anomalies or abnormal trends. Collaboration between maintenance tools is essential to the successful implementation and execution of predictive insights-based preventive maintenance activities. Support staff or modernized frameworks are cautioned whenever the situation allows, and blemishes or irregularities are found, which prompts brief activities including assessments or substitutions. This procedure enjoys a few benefits. Proactive support broadens the existence of gear and brings down fix costs by limiting margin time and forestalling functional interferences. By focusing endeavors on gear that is probably going to breakdown, diminishing unnecessary margin time, and upgrading profit from venture, prescient support the executives additionally makes cost decreases conceivable. By predicting potential issues or wellbeing risks, a safer work environment might be made, prompting improved security. Worked on support methods that expand planned free time and lessen startling personal time by using verifiable data and AI procedures to increment proficiency. Besides, this approach's information-driven experiences advance greatness in tasks, enhance development opportunities and guide direction [10].

To address the critical need for reliable maintenance management within Zigbee-enabled smart home networks, the proposed research focuses on developing a machine learning-driven technique based on defect prediction models. It is turning out to be increasingly vital to ensure the progression and constancy of these frameworks as shrewd home organizations are utilized to robotize and manage the Web of Things gadgets for further developed solace and energy productivity. To cut down on costs and downtime caused by equipment failure, the suggested strategy makes use of advanced analysis and predictive maintenance techniques. XGBoost, as well as Firefly Enhancement, are two instances of cutting-edge AI calculations that are utilized to distinguish framework disappointments and empower deterrent support. In the smart home network, data is pre-processed to extract relevant information that is necessary for failure prediction from sensors and tracking devices. The XGBoost procedure is utilized to track down complex connections in the information to further develop forecast capacity, though Firefly Advancement is utilized to augment model execution through hyperparameter changes. To prepare the models, verifiable information is utilized to find drifts that could highlight potential disappointments or glitches in Zigbee-empowered gadgets. The proposed system, written in Python, endeavours to consistently distinguish and analyse blemishes in shrewd home machines by breaking down a huge dataset. The strategy aims to provide precise and timely forecasts that make planned repair interventions possible by incorporating XGBoost and Firefly Optimization into the fault forecasting models. Eventually, the recommended work intends to ensure the constancy and life span of smart home gadgets while diminishing expenses related to support and inaccessibility. By perceiving the rising interest in proactive support ways to deal with ensure the most extreme execution and client prosperity, this examination progresses prescient upkeep strategies inside the structure of smart home environmental factors.

The following is the proposed work's primary contribution:

- The proposed work enhances predictive maintenance for Zigbee-enabled smart home networks, reducing processes while minimizing loss.
- To increase defect prediction precision, machine-learning methods like XGBoost and Firefly Optimization are employed.
- Firefly Optimization optimizes hyperparameters for maximum efficiency of models and ambient adaptability.
- Implementing preventative servicing practices utilizing fault prediction models reduces repair expenditures and increases the usefulness of Zigbee-enabled equipment.
- The proposed work optimizes predictive maintenance and enhances user interaction with smart home networks, ensuring homeowners have continuous access to services and functionality.

The structure of the suggested paper will be as follows: An overview of maintenance prediction management in Zigbee-enabled smart home networks will be given in Sect. 1. Relevant works for Sect. 2 are provided. Section 3: Challenges of current approaches. The approach, including data collecting, preprocessing, and the use of XGBoost structures for failure prediction, will be covered in Sect. 4. The experimental findings and assessment metrics will be shown in Sect. 5. The study will be concluded and new research areas will be suggested in Sect. 6.

2 Literature Review

Abdallah et al. [11] proposed a method for fault diagnosis in wind turbine. Developing systems with decision support that can assist engineers and operators in managing these assets is crucial for the optimal functioning and upkeep of wind energy infrastructures. Given the variety of assumptions included in the combined data, the state of understanding regarding the structures and parts of wind turbines, and also the continuously fluctuating operating and ecological demands, this work is especially difficult. Here, they suggest using a decision tree-based technique of learning to spread wind turbine information to find anomalous functioning, trends, discrepancies, flaws, and destruction. Decision trees are used because they are typically simpler to utilize and understand compared to other quantitative data-driven techniques. Moreover, the data gathering includes information from architectural and environmental surveillance infrastructure, which fits in well with the Big Data space since it continually samples massive volumes of data at a rapid rate across many different wind turbines. To figure out the paths connecting excessive vibration faults and their potential root causes, they first analyze several decision tree algorithms that have previously been put forth by the fields of machine learning. Next, instruct an ensemble-bagged decision tree algorithm using a sizable condition assessment information set coming from a floating wind farm that includes 48 wind turbines. Subsequently, they present an overview of a framework that uses cloud-based Apache Hadoop technology for managing and storing enormous amounts of data, along with Apache Spark allowing efficient execution of machine learning algorithms, to perform decision tree learning within the framework of big data cloud computing.

Dorgo et al. [12] proposed a method for fault classification. In industrial operations, alarm messages are intended to highlight irregularities that call for prompt examination or action. But in reality, process operators design alerts unnecessarily and indiscriminately, which leads to a lot of bothersome and noisy sirens that serve as merely a means of attention. There are several methods for retrospectively processing alarm data, such as modifying current alarm parameters to include time lapses and inactive zones. Alternatively, a method for designing informative alarm messages for identifying faults is provided in this paper, which takes into account the fact that the alarm messages that initially occur ought to remain greatest for recognizing errors and identification, rather than separating or altering already-existing signals. The decision tree classification algorithm, a machine learning approach used in this approach, produces linguistically understandable predictions despite requiring changes to the observed procedure variables. Additionally, a moving window-based data preprocessing technique is described enabling a secure online application to execute predefined alarm messages for defect detection. The examination of a widely recognized benchmark simulation for a vinyl-acetate production technique, that's complicated and is thought to be enough for evaluating alarm systems, is used to show the efficacy of the suggested methodology. It is possible to assign ordinary functioning and fault-specific phases to historical process outcomes by using process-specific information. It needs to be possible to identify and isolate defective situations in alarm production systems.A labelled dataset may be used to determine the best "cuts" or alert limits for fault categorization using decision trees. The findings are relevant to many different sectors using online control systems, but they are particularly pertinent to the chemical sector.

Tariq et al. [13] suggested a security paradigm. The Internet of Things infrastructure is installed in the intricate industrial setting of the modern era better handling of devices, immediate time operational visibility, and predictive maintenance. Private interconnection is required to be achieved across a variety of current, disparate gadgets and information sources to fully release the targeted relevance of its policy. The study's goals throughout the conception stage were to (a) require accessibility restrictions be based on the occurrence of unusual device behaviours that might indicate a security breach; and (b) guarantee system safety by ongoing surveillance of connected equipment and information. This paper proposes a policy-driven, lack-of-trust protection system that can quarantine insecure devices, demonstrate instrument utilization of authorized enterprise functions, handle multiple points of vulnerability, and initiate computerized cautions along with rules approval for data management, hardware, software, and network connectivity. An experimental system was set up for handling outgoing risk administration, proactive inspection of bots, passive oversight, and gadget linkages. A permanent and comprehensive picture of all assets especially unknown ones, is provided by this ecosystem. By avoiding known anomalous traps, a consistent flow of trustworthy and verified data has aided in the development and adjustment of a scalability deployment approach. To evaluate the suggested methods, real data was compiled and examined. The efficacy of the suggested technique has been demonstrated by a comparative examination of "device vulnerability opinion, assault path assessment, regulated perspective on gadgets, extensive exposure assessment, and innovative dissemination of cyber risk." The assessment's good outcome contributed to the creation of an effective and safe Internet of Things environment.

Azimi et al. [5] recommended a optimal planning for smart home network. Establishing smart buildings and houses is a crucial part of creating smart cities, and from an energy standpoint, creating and putting into place a smart home area energy management system is essential. The home area energy management system, which functions as a microgrid, must incorporate a variety of electrical gadgets, locally distributed/renewable energy resources, and energy storage devices to be functional. However, because of the necessary sensors, network connectivity, and computing load, gathering and analysing the data related to these devices and assets is difficult. The physical prerequisites for managing the data have been given by the Internet of Things along with cloud computing techniques; nonetheless, they require appropriate optimization/management techniques. This study presents an intelligent cloud management and allocation technique that can dynamically distribute and manage cloud resources for the energy administration system. For the legitimate data from the source, every day's demand for assigning virtual computers to each client is given. The successful execution of the suggested service, considering that it is executed wirelessly and relies on internet-of-things platforms and sensor networks as its primary technologies, is contingent upon the strategic distribution of supercomputer resources and scheduling algorithms. This article describes the development of a residential region energy administration system that makes use of cloud services to improve the processing of information efficiency and precision.A suggested management protocol offers the best timetable for the electrical appliances in smart residential houses to operate daily based on welfare metrics. A home area energy management system processes information collected individually, and the hourly ideal usage of devices, era, and storage facilities is scheduled in the cloud. The proposed system consists of three layers, sensors connected to the home appliances along with generation/storage components, local fog nodes, as well as a cloud. This program for the home area energy management system makes use of both neural networks and genetic algorithms. The neural network has become used to forecast how much labour will be required in response to user inquiries.Enhancing both load factor and financial effectiveness is regarded as the goal purpose that genetic algorithms are used to achieve. The MATLAB platform is used for numerical research, and the outcomes are compared to those obtained using more traditional techniques.

Wang et al. [14] suggested anearly fault detection. Precisely forecasting quality results from observed signals is one of the objectives of ultrasonic welding tracking. But most of the time, it is not enough to know that the ultrasonic welding procedure has failed. To address process issues, contemporary automated procedures ought to evaluate signal data and take appropriate action. Determining the point at which an aberrant event begins, or whenever a procedure's indicator diverges from an acceptable ultimate quality output, allows for control measures or root cause analysis for regaining compliance. To track and identify this moment, an LSTM, or long short-term memory, recurrent neural network has been suggested for tracking ultrasonic welding along with additional time-series data. With continuous data, this deep neural network undergoes training to determine better results. An LSTM network that categorizes the quality of the final product of ultrasonic welding processes was put into place to determine the origin of anomalous process signals. The period during which the procedure signals merge to the final anticipated quality classification is calculated using a step-by-step cross-entropy computation using the categorization chances. For feed for this network, the system's tracking indicators and their sample period are split into limited segments. Utilizing the cross-entropy of the categorization estimations, the length of the segmentation at which the procedure's signal initially settles to the ultimate classification forecast is found. Robotic mobility failure identification and ultrasonic welding inspection techniques are used to illustrate this process. The instances demonstrate that an LSTM network may forecast ability with high accuracy and that its classification phase of convergence corresponds with the variance in ultrasonic welding performance variables. Furthermore, it was demonstrated that particular robotic mobility errors were linked to classification convergence times, which is helpful information for adaptive learning. This study offers the information required for adaptable control approaches and accomplishes early event detection and deep learning excellence forecasting for quality classification tasks. The present study shows how effective categories may be reliably forecasted from various input signals despite the need for typical feature engineering. Moreover, a cross-entropy in the categorization possibilities is computed to ascertain the length of time phase during which the input signal initially merges towards the end forecast.

Alzoubi et al. [15] recommended a machine learning approach for smart home network. The capacity to supply oneself with energy directly correlates with the expansion of one's satisfaction. Because contemporary technology allows individuals to build and improve their standards of life more quickly, valuable power has long been a desired expansion because of the usage of smart homes and constructions. There is not enough energy since the requirement for it is higher than the supply. New tactics are being created to meet the growing need for energy. Residential energy usage is between thirty and forty percent in many places. Smart homes are becoming increasingly common, which has increased the demand for intelligence in areas like asset management, environmentally friendly automation, security, and health care tracking. During this study, energy administration is being used to address the efficiency of energy use. Data fusion has gained a lot of attention lately when it comes to energy-efficient building construction. The information about the fusion method offered by the suggested study was used to calculate the precision and error rate of consumption of electricity estimates. The results of the simulation are contrasted against the results of previously published techniques. Furthermore, it boasts an accuracy rate of 92%, higher than any other method that has been historically documented. Households are finding it more and more crucial to control their power expenses as a result of rising electricity use and the introduction of distributed new energy sources. The implementation of a residential energy monitoring system represents a workable resolution to these problems.

Wardet et al. [16] proposed a deep learning approach for fault detection. Applications of deep learning are being utilized to address issues in important fields. Therefore, to make sure that the desired behaviour is delivered, developers must debug their systems. However, debugging DNNs is challenging and costly. The history of the DNN program's inability to identify the specific component is lost when failure symptoms or dissatisfied accuracy are reported after training. Additionally, various kinds of flaws can occasionally be found in deep learning programs. To tackle the difficulties associated with troubleshooting DNN models, they provide a unique data-driven method that utilizes model characteristics to identify issue trends. During DNN training, this approach identifies these characteristics, which stand for a semantic description of errors. These characteristics serve as a learning sample for the method, which learns and infers DNN failure patterns. Additionally, technology does not require explicitly generated translations; instead, it effortlessly links the apparent signs of bugs to their underlying causes, allowing developers to take the appropriate action to correct errors. They assess our method on both wild-type and modified models. Results show that our method is capable of accurately identifying and diagnosing various bug kinds. This approach outperformed previous research for modified models in terms of accuracy, precision, and recall. Furthermore, the technique outperformed the latest developments concerning precision and efficacy for real-world models. An LSTM model is used by Deep-4Deep to instinctively find and recognize DNN problems.

The associated research described in this article addresses a variety of uses of sophisticated technology, such as deep learning, machine learning, and the Internet of Things, for solving problems in a variety of domains, including industrial processes, managing energy in smart homes, and buildings, IoT security, wind energy infrastructure, and deep learning model troubleshooting. The studiesoffer novel approaches and tactics to tackle problems in several areas, including deep learning model debugging, smart home energy efficiency, and wind energy infrastructure administration. The literature review presents a choice tree learning approach for issue distinguishing proof in windmill checking the information in the setting of wind energy, offering important information concerning high vibrations and their potential causes. It also explains how to use decision tree-based classifiers to improve defect recognition and classification in industrial processes, preserve the integrity of process variables, and generate useful warning signals at the same time. The review utilizes cloud-based instruments for overseeing dangers and contraption check to introduce a strategy driven, zero-trust guarded worldview for IoT security that gets associated gadgets and information. It likewise offers a sharp technique for overseeing and designating assets progressively in cloud-based energy organization frameworks, limiting energy use as well as arranging strategies for wise lodging structures. The exploration likewise presents a profound learning-based technique to follow the ultrasonic welding strategy. It utilizes long transient memory organizations to distinguish atypical interaction signals and figure quality results accurately. Adaptive management and prompt intervention are made possible by this. Finally, it proposes a data-driven strategy that outperforms previous approaches in terms of precision and efficacy to address the challenges of diagnosing deep neural network systems by utilizing model attributes [17]. Generally speaking, by proposing imaginative suggestions and reactions to testing certifiable issues, the work progresses research in many fields. Even though the connected work employs cutting-edge technology to address a wide range of issues in a variety of fields, some constraints must be taken into account. These include the possibility of privacy and security issues in IoT ecosystems, the adaptability and generality of the suggested methods, and the requirement for additional testing and verification in real-world settings to assess their usefulness and effectiveness.

The collection of research papers reviewed provides innovative solutions to various challenges across different domains, including fault diagnosis in wind turbine systems, fault classification in industrial operations, security paradigms for the Internet of Things (IoT), optimal planning for smart home energy networks, early fault detection using deep learning techniques, and deep learning model debugging. Each paper presents novel methodologies and approaches tailored to address specific issues within its respective field. For instance, Abdallah et al. propose a decision tree-based approach for fault diagnosis in wind turbines, while Dorgo et al. focus on designing informative alarm messages for fault identification in industrial processes. Tariq et al. suggest a policy-driven security system for IoT, Azimi et al. recommend an intelligent cloud management system for smart home energy management, and Wang et al. propose an LSTM-based method for early fault detection in ultrasonic welding processes. Alzoubi et al. suggest a machine learning approach for smart home energy networks, and Wardet et al. propose a deep learning approach for DNN debugging. Overall, these studies contribute valuable insights and methodologies to their respective fields, though considerations such as privacy and security in IoT ecosystems and the need for real-world testing and verification remain important for further advancement and application of these techniques.

3 Problem Statement

The current methods for fault prediction and maintenance planning in Zigbee-enabled home automation systems may have flaws, such as the use of oversimplified models that fail to capture intricate relationships, a lack of information that makes it hard to understand models' predictions, and a lack of capacity for managing large datasets. Additionally, these strategies may struggle with unbalanced data distributions and may require a significant amount of processing power to train and implement, limiting their application in actual smart home settings [18].To overcome these restrictions, the suggested technique uses machine learning during periodic upkeep. Given the Zigbee-enabled smart home gadgets, the suggested focus represents a substantial smart-based intelligence-driven technique for environmental opinions. Firefly Optimization, or XGBoost, is used in the concept to anticipate system issues and cut costs and delays. The utilization of state-of-the-art AI methods, data preprocessing, and hyperparameter acclimation to guarantee routine upkeep and, subsequently, the life span and reliability of smart home gadgets is an original element of this system.

4 Enhancing Predictive Maintenance in Zigbee-Enabled Smart Home Networks Using XGBoost Algorithm for Fault Prediction

The proposed method for improving precautionary breakdown effectiveness in Zigbee-enabled smart home networks is a complete procedure that includes unique approaches such as Firefly Optimization and XGBoost to increase fault prediction precision. First, sensors deployed within the smart home network gather data on ambient conditions, operational variables, and equipment efficiency metrics. Preprocessing procedures such as managing missing values and reducing noise assist in data confidentiality. Then, utilizing feature engineering methodologies that do not use standard procedures, valuable features are retrieved that identify sequences indicating conceivable anomalies or faults. The dataset will be separated into sets for testing and training to construct and evaluate the model. XGBoost, a gradient-enhancing technique, is used for developing an ensemble of decision trees on arbitrary parts of the training data, as opposed to utilizing each tree individually. By reducing the loss function, XGBoost's iterative design enables the model's capacity for prediction to be continuously improved. To improve the accuracy and resilience of the model, Firefly Optimization is also used for hyperparameter tuning, whereby parameters like the quantity of trees as well as their maximum depth are optimized. The testing dataset is used to evaluate the accurate prediction and generalization efficacy of the trained XGBoost model. Through the integration of innovative machine learning approaches and optimization models, the proposed methodologywhich is depicted in Fig. 1 of the framework's architecture diagramensures the efficacy of the proactive upkeep technique in Zigbee-enabled smart home systems by achieving better fault forecasting abilities.

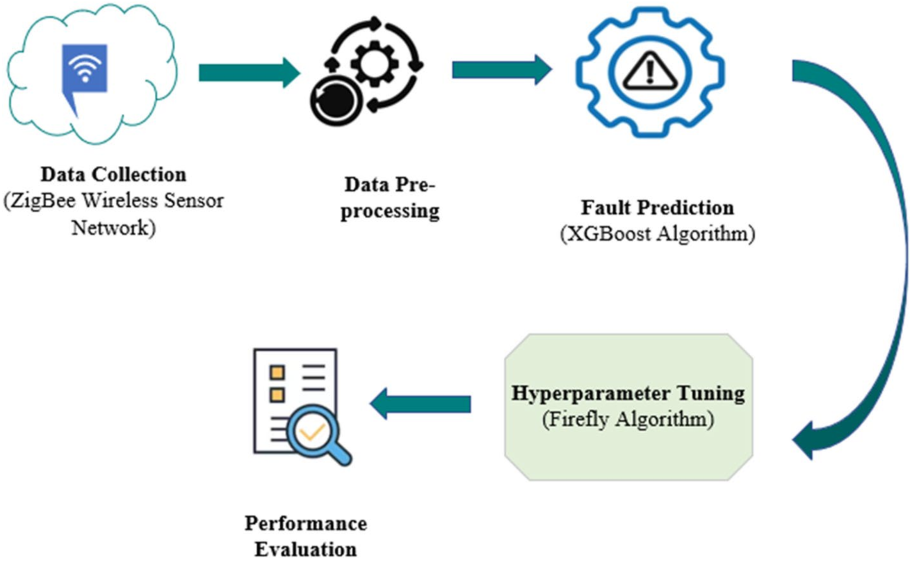

Fig. 1 Proposed XGBoost method fault prediction framework

4.1 Data Collection

A ZigBee wireless sensor network was used to monitor the humidity and temperature levels throughout the residence. The environmental temperature and moisture content were transferred by each wireless node in approximately 3.3 min. The wireless information was subsequently averaged across intervals of ten minutes. Using m-bus energy meters, the energy information was recorded every ten minutes. Employing the date and time column, the weather from the closest airport weather station has been merged with both experimental data sets after being collected through a public collection of information from consistent predictions. The data set contains two random variables to evaluate regression models and remove non-predictive features (parameters) [19].

4.2 Data Pre-processing

When erroneous, insufficient, incorrect, insignificant, or absent parts of data are found, they are modified, replaced, or deleted as needed. This process is known as data cleaning. In machine learning, irrelevant or erroneous input might result in the creation of the wrong model. To ensure the accuracy and dependability of the data gathered for Predictive Maintenance Management in Zigbee-enabled Smart Home Networks, data cleansing is essential. It involves dealing with outliers, resolving missing values, and eliminating discrepancies. Imputation, in which missing points of information are substituted with approximated values, is a popular method for addressing value gaps. Mean imputation is a basic imputation technique in which the information that is accessible means is used to substitute missing values. Equation (1) provides a numerical illustration of mean imputation.

$$\widehat{m_a} = \frac{1}{v}\sum_{b=1}^{v} m_b \tag{1}$$

where, m_b denotes the number of accessible data values and $\widehat{m_a}$, is the approximated value that represents the missing information point m_a.

Equation (1) represents a method called mean imputation, which is a simple technique used to handle missing data values. In this equation, $\widehat{m_a}$ represents the approximated value for the missing data point m_a. It is calculated as the average of the available data values, denoted by m_b, where v is the total number of available data values. Essentially, mean imputation fills in missing values with the average of the known values. This approach assumes that the missing values are missing at random and that the mean of the available data is a reasonable estimate for the missing values. However, it's important to note that mean imputation can lead to biased estimates and inaccurate conclusions if the missing data mechanism is not random or if there is substantial variability in the data.

4.3 XGBoost Method for Fault Prediction

Extreme Gradient Boosting, or XGBoost, is an effective and frequently employed machine learning algorithm that has gained appeal for its effectiveness in forecasting applications, particularly those involving organized or structured data, such as the one proposed for optimizing servicing forecasts in Zigbee-enabled smart home networks. To forecast mistakes or malfunctions throughout the smart home network, XGBoost chooses pertinent characteristics from the previously processed information that is most instructive. XGBoost improves learner efficacy and efficiency by continually constructing new decision trees to fit values using multiple phases of gradient-boosting architectures. XGBoost strives more to equalize variability and biases than Friedman's gradient boosting, relies on Taylor approximations to derive the loss function, and usually uses fewer decision trees to attain higher accuracy.

XGBoost (Extreme Gradient Boosting) is leveraged for fault prediction in servicing forecasts through several avenues: firstly, it offers insights into feature importance, allowing maintenance teams to prioritize tasks based on factors with the greatest impact on fault occurrence, thus optimizing resource allocation. Secondly, XGBoost enables early detection by identifying patterns indicative of impending faults, facilitating proactive maintenance to mitigate downtime and prevent costly repairs. Thirdly, it supports predictive maintenance scheduling by forecasting when maintenance will likely be required based on historical data and current conditions, optimizing preventive maintenance efforts. Lastly, XGBoost aids in resource allocation by predicting the likelihood of faults in different components or systems, ensuring that maintenance resources are focused where they are most needed, optimizing time, manpower, and materials. This comprehensive approach enhances the reliability, efficiency, and longevity of equipment and systems by optimizing servicing forecasts through the predictive capabilities of XGBoost.

The Fig. 2 depicts the XGBoost architecture diagram. $D = (xi, yi)(|D| = n, xiRm, yiR)$ is the equation given an experiment collection with n samples and m features, whereby x is the eigenvalue and y is the real value. The ultimate projected value is obtained by adding together the outputs of K trees, as stated in Eq. (2).

$$\widehat{y_i} = \sum_{k=1}^{k} f_k(x_i), f_k \in f \tag{2}$$

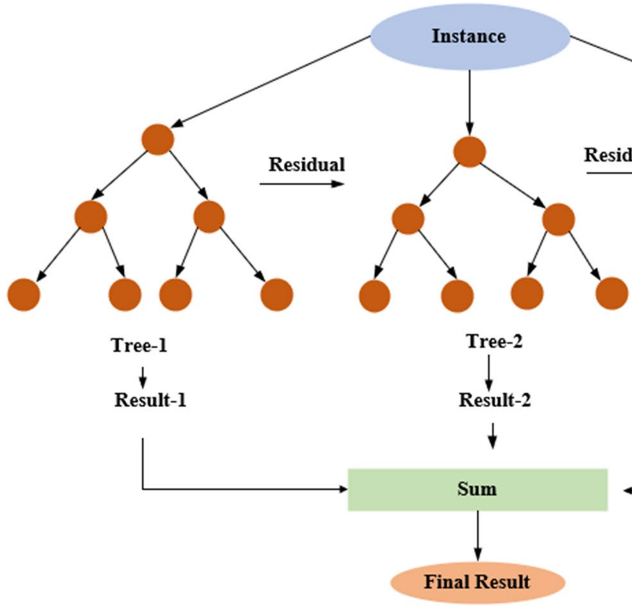

Fig. 2 XGBoost architecture

Equation (2) illustrates the ensemble learning method known as bagging, specifically applied to decision trees. It represents the process of combining the predictions from multiple decision trees to generate a final prediction. Each decision tree in the ensemble contributes its prediction for a given input, and the final predicted value is obtained by summing these individual predictions across all trees. This technique aims to enhance the accuracy and stability of the predictive model by leveraging the diversity of predictions generated by different trees trained on various subsets of the data or using different randomization strategies.

The decision trees in set F are shown below in Eq. (3).

$$f = \{f(x) = w_{q(x)}\}(q : R^m \to T, w \in R^T \tag{3}$$

When any of the trees is represented by $f(x)$ and $wq(x)$ represents the amount of weight among the leaf nodes. Each tree's structure, or q, links each sample to a particular leaf node. T denotes the total amount of leaf nodes. Consequently, the expected value of XGBoost is equal to the sum of the values of all the leaf nodes in each tree. Given that learning these k trees is the goal of the model, the objective function beneath is decreased that is shown in Eq. (4).

$$L^{(t)} = \sum_{i=1}^{n\_} l(y_i, \hat{y}_i) + \sum_{1^k=1}^{k} \Omega(f_k) \tag{4}$$

Frequently occurring loss functions include the logarithmic, square, and exponential functions. L represents the reduction in the discrepancy between the calculated values $\hat{y}_i$

and the actual value y_i. Ω to avoid excessive fitting, normalization is applied to calculate the decision tree's consequence is explained in Eq. (5).

$$\Omega(F) = \gamma T + \frac{1}{2}\lambda\|w\|^2 \tag{5}$$

T represents the number of leaf nodes, and the hyper-parameter determines how complex the model is. The leaf weight constraint coefficient is a constant in most cases. The parameters determine the level of detail of the framework and are frequently given through experimentation. During training, a new tree is added to handle leftovers from the previous session. Thus, whenever there are t trees, the framework is shown below in Eq. (6).

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_k\left(x_i\right) \tag{6}$$

The function is created by changing the objective of the function (4)–(7).

$$L^{(t)} \approx \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t\left(x_i\right) + \frac{1}{2} h_i f_t^2\left(x_i\right) \right] + \Omega\left(f_k\right) \tag{7}$$

wherein the loss function's initial derivative is denoted by, g_i and its second derivative by hi Because the remaining value has no bearing on the objective function's effectiveness, it is deleted from the forecast score $\hat{y}_i^{(t-1)}$ and y_i.

$$L^{(t)} = \sum_{i=1}^{n} \left[g_i f_t\left(x_i\right) + \frac{1}{2} h_i f_t^2\left(x_i\right) \right] + \Omega\left(f_k\right) \tag{8}$$

Equation (8) represents the overall objective of the XGBoost algorithm, which aims to minimize the cumulative loss function across all data points. The loss function is composed of two terms: the first term evaluates the errors between the predicted and actual values, weighted by the gradients of the loss function, while the second term accounts for the curvature of the loss function by incorporating second-order gradients. The objective function also includes a regularization term to prevent overfitting and promote model simplicity. Ultimately, XGBoost iteratively improves its ensemble of decision trees by optimizing this objective function, resulting in a model that accurately predicts outcomes while avoiding excessive complexity.

The ideal leaf node value is determined by converting every iteration of the underlying tree structure into each iteration for the leaf nodes by $w_j = -\frac{G_j}{H_{j+\lambda}}$. By adding the optimum value to the desired operation, the whole objective's function is generated, where Gj is $\sum_{i=1}^{I_j} g_j$ and Hj is $\sum_{i=1}^{I_j} h_j$ is shown in Eq. (9).

$$Obj = -\frac{1}{2} \sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda} + \gamma T \tag{9}$$

Equation (9) defines the objective function used in the XGBoost algorithm, which aims to optimize the construction of decision trees by determining the ideal values for the leaf nodes. The objective function consists of two main components: the first term represents the reduction in the loss function achieved by splitting the data into leaf nodes, calculated as the sum of squared gradients divided by the sum of second-order gradients plus a regularization parameter λ to prevent overfitting. The second term penalizes the complexity of the model by adding a regularization term γ multiplied by the total number of leaf nodes T.

Together, these components form the objective function that XGBoost seeks to minimize during the training process, guiding the algorithm to construct decision trees that effectively capture patterns in the data while avoiding overfitting and excessive complexity.

XGBoost creates a group of decision trees, each of which fixes the mistakes caused by the ones before it. The converted features and matching target labels are used to train the XGBoost model. The model may be used to forecast fresh, unobserved data once it has been trained. All things considered, XGBoost works well because it can effectively integrate the advantages of several decision trees while handling problems with overfitting, training rate, and scalability. XGBoost can function as a reliable and effective predictive modelling tool in the planned work over ongoing maintenance improvement in Zigbee-enabled smart home networks. It can identify intricate patterns in the data and provide accurate forecasts for identifying faults and upkeep scheduling.

Fault Prediction Model is gives as follows,

$$\hat{y}_i = f\left(x_i\right) \tag{10}$$

where $\hat{y}_i$ represents the predicted fault occurrence for sample (x_i) in the smart home network, based on the machine learning model f.

Zigbee-enabled Sensor Data Fusion is given by,

$$D = (x_i, y_i) \tag{11}$$

where D represents the dataset consisting of N samples with features x_i collected from Zigbee-enabled sensors and corresponding maintenance labels y_i facilitating fault prediction model training.

Cost Function for Maintenance Activities are gives as follows

$$\mathrm{cost}(x_i) = \sum_{j=1}^{M} C_j \tag{12}$$

where cost (x_i) epresents the total cost associated with performing maintenance activities for sample x_i in the smart home network.C_j denotes the cost of each individual maintenance action, such as repair or replacement of components, ensuring that the overall cost of maintenance is accurately accounted for in the optimization process.

Reliability Assessment Equation is given by,

$$R(t) = e^{-\lambda t} \tag{13}$$

where $R(t)$ represents the reliability of components or devices in the smart home network at time t. The equation incorporates the failure rate λ, indicating the likelihood of a component or device failing within a given time frame. By assessing reliability, maintenance schedules can be optimized to minimize downtime and ensure the smooth operation of Zigbee-enabled smart home networks.

4.4 Firefly Optimization

Hyperparameter altering is used to enhance the ensemble tree models' performance. The suggested work takes advantage of firefly optimization. This method effectively searches the hyperparameter space for ideal configurations, improving the effectiveness of the suggested preventative management approach in Zigbee-enabled smart home networks. Brighter fireflies within the search area indicate better solutions, and the FA iteratively adjusts their locations. This makes it possible to experiment with different combinations of hyperparameters to increase the precision of forecasting faults and optimize maintenance.The "nature-inspired" Firefly algorithm is derived from the way flies behave. Algorithms with inspiration from nature are widely employed throughout the machine learning process [20]. The natural lights that fireflies generate from their bodies aid in their ability to attract and locate other flying partners. They may capture victims and defend themselves against predators with its assistance. Three main presumptions underpin the algorithm's design. The unisex synthetic fireflies are attracted to people regardless of gender. A firefly's attraction is directly correlated with the intensity of the light it emits, and as it moves away from another, the light is absorbed by the air, making it less appealing. Because all fireflies generate light, the majority of their neighbours are drawn to the one that emits the most illumination. In contrast, all fireflies travel haphazardly in any direction if there isn't a single light firefly in the area. The objective function in the algorithm that has to be improved is the flashing light's brightness, which serves as the attraction criterion. The firefly algorithm's pseudo code appears in Algorithm 1.

Algorithm 1 Pseudo code for firefly algorithm

```
Objective function generates duration, z = (f_1, f_2, f_3, ... f_n)
Build machines (a = 1, 2 .... o)
Build task series (b = 1, 2, ... u)
Compute generate spanning (f_1, f_2, f_3, ... f_n) for the whole number
While Gen.<MaxGendo
          for all task series j = (1,2, 3 ...., n) do
            for all numerous dimension Q_(a,b)do
               Navigate the firefly in a d-dimensional area
               Calculate attractiveness depending on distanceS_ab
               Assess maximum duration
     Evaluate light intensity
     Choose work schedules and quantities for Gen. +1R
```

Using firefly optimization in the context of predictive maintenance optimization in Zigbee-enabled smart home networks offers several advantages. Firefly optimization is a nature-inspired metaheuristic algorithm that mimics the behavior of fireflies in nature, where fireflies adjust their flashing patterns to attract mates. In the context of optimization problems, firefly optimization excels in searching for optimal solutions in complex, multi-dimensional search spaces. Its ability to efficiently explore the solution space and adaptively adjust the intensity of light (i.e., attractiveness) between solutions makes it particularly well-suited for fine-tuning parameters and optimizing models in machine learning-driven approaches. By leveraging firefly optimization, the optimization process can effectively identify the most suitable parameters for fault prediction models, thereby improving the overall performance and accuracy of predictive maintenance in Zigbee-enabled smart home networks. Additionally, firefly optimization is inherently parallelizable and computationally efficient, making it suitable for optimizing large-scale, real-time systems like smart home networks. Overall, integrating firefly optimization into the optimization framework enhances the efficacy and efficiency of predictive maintenance strategies, ultimately leading to better performance and reliability of smart home networks.

5 Results and Discussion

The suggested study effectively illustrated the use of XGBoost methods for Zigbee-enabled smart home network malfunction prediction. The XGBoost algorithms were trained and assessed by utilizing an extensive dataset that included weather information from an airport close to a weather station, energy data recorded by m-bus energy meters, and temperature and humidity variables recorded by a ZigBee wireless sensor network in the home. The results demonstrated an intriguing degree of accuracy in terms of automatically identifying and diagnosing smart home device issues. XGBoost models enhanced fault prediction reliability as well as dependability by effectively capturing complex connections in the data.

5.1 Performance Evaluation

The efficiency of the suggested XGBoost Method is contrasted with that of the RNN, SVM, LSTM, and Naive Bayes techniques. Accuracy, precision, recall, and F1-score were used as comparative assessment criteria. The parameters that were used for assessing the model are displayed below.

5.1.1 Accuracy

A commonly employed metric for evaluating how well classification jobs work. is precision. By splitting the entire number of forecasts by the number of correct predictions, the accuracy is calculated. An Eq. (10) is used to describe it.

$$Accuracy = \frac{UG + IV}{IV + LO + UG + SV} \tag{14}$$

In this case, "UG" denotes true negative, "IV" denotes true positive, "LO" denotes false positive, and "SV" denotes false negative.

5.1.2 Precision

Precision is a metric used to assess a classification model's accurate predictions. It is particularly important in cases when false positive errors are costly or undesirable. To calculate precision, utilize the following Eq. (11).

$$Precision = \frac{\mathrm{IV}}{\mathrm{TD} + \mathrm{LO}} \tag{15}$$

where "FP" stands for false positive and "IV" for genuine positive. The overall number of instances that are positive in the dataset is indicated by TD.

5.1.3 Recall

Recall is a metric used to assess a classification model's ability to precisely identify each pertinent instance of a given class. It is also commonly referred to as sensitivity or real-positive rate. Recall is computed using the following Eq. (11).

$$Recall = \frac{\mathrm{IV}}{\mathrm{IV} + \mathrm{SV}} \tag{16}$$

5.1.4 F1 Score

An adequate evaluation of the categorization model's efficacy is provided by the F1 score, a metric that incorporates accuracy and recall. It is particularly useful when attempting to strike a compromise between preserving accuracy and minimizing false negatives (recall) and erroneous findings (precision). The following is Eq. (12), which determines the F1 score.

$$F1score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{17}$$

Accuracy, Precision, Recall, and F1 Score constitute certain of the performance metrics of the proposed XGBoost model presented in Fig. 3. The F1 Score is the calculated mean of Precision and Recall. Accuracy is the proportion of properly categorized cases. Precision is the proportion of correctly predicted positive cases between all expected positive instances. Recall is the proportion of positively predicted events among all actual positive experiences. The XGBoost model's accuracy, recall, and F1 Score values demonstrate that it is effective at accurately detecting positive events while reducing inaccurate results and negative outcomes. The accuracy of 98% suggests an exceptional degree of prediction accuracy.

Table 1 displays the performance parameters for several machine learning models, such as RNN, Naive Bayes, SVM, and LSTM, as well as the suggested XGBoost model. The F1 Score, calculated as the balanced mean of Precision and Recall, provides a balanced measure of a model's efficacy. After testing all of the models, the proposed XGBoost approach has the highest accuracy (98%), suggesting that its forecasts are the most precise overall. It performed better than with previous techniques in terms of accuracy, recall, and F1 scores, proving its capacity to correctly classify positive occurrences while reducing erroneous

Fig. 3 Performance of the proposed XGBoost method for fault prediction

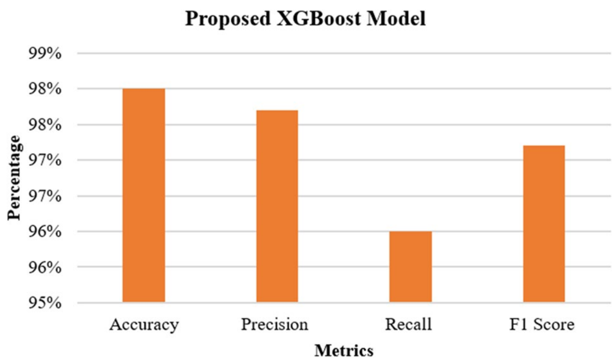

Table 1 Performance comparison of proposed method with existing method

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
RNN [21]	82.5	81.4	79.1	79.3
Naive Bayes [22]	91.2	90	88	89
SVM [23]	94	92.3	91	90
LSTM [24]	95	94.2	92	93.1
Proposed XGBoost model	98	97.7	96	97.2

discoveries and false negatives. The suggested XGBoost model performed well over other models across all measures, demonstrating higher predictive ability.

Figure 4 compares the performance parameters, such as accuracy, precision, recall, and F1 score, of several machine learning models. Each model, comprising RNN, Naive Bayes, SVM, LSTM, and the suggested XGBoost Model, is assessed for its ability to produce correct predictions. Accuracy represents the total accuracy of forecasts, whereas precision is the fraction of accurate positive forecasts amongst all positive predictions. Recall refers to the fraction of genuine positive forecasts among all real positive cases. The F1 score is the equilibrium value of accuracy and recall, giving an accurate evaluation of the effectiveness of a model. The figure clearly shows that the proposed XGBoost Model achieves the highest accuracy of 98% across all metrics, demonstrating its superior predictive capability compared to other models like RNN, Naive Bayes, SVM, and LSTM.

Figure 5 shows the process of training and evaluating the accuracy ratings of an algorithm for machine learning at different phases of training. The training accuracy of the model indicates its efficacy on the training dataset at various training epochs, whereas its testing precision indicates its effectiveness on an independent testing dataset. The figure indicates that the precision of the model changes over time throughout training, revealing facts about its learning process and generalization ability on previously unknown data.

Figure 6 shows both the training and testing loss rates for a machine learning model at various stages of training. The training loss is the difference between anticipated outputs and actual objectives upon the training dataset, whereas the testing loss shows the model's efficacy on a different testing dataset. Lower loss values suggest a better alignment between

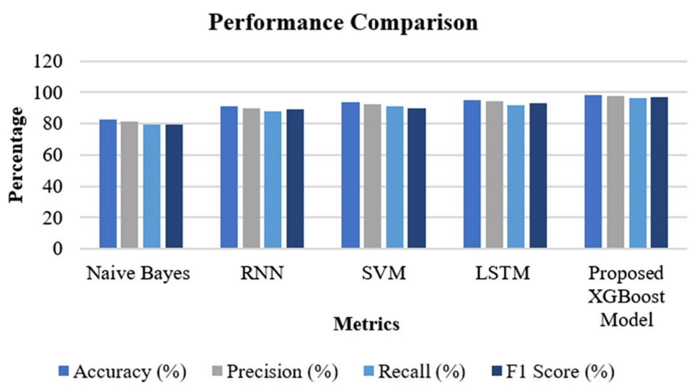

Fig. 4 Performance comparison of proposed XGBoost method with existing method

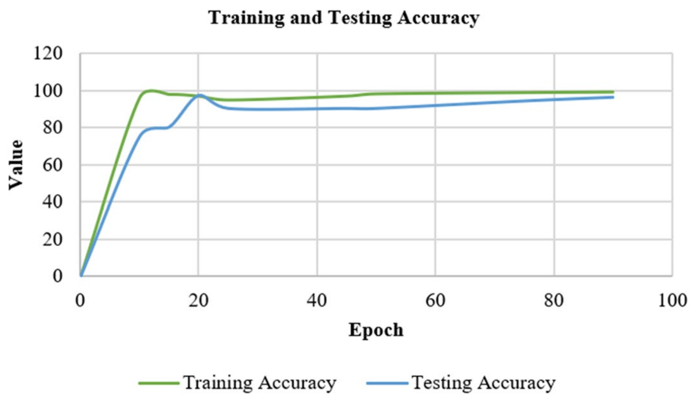

Fig. 5 Graphical depiction for training and testing accuracy of proposed XGBoost method

Fig. 6 Graphical depiction for training and testing loss of proposed XGBoost method

projected and actual values. The graph indicates that the model's error loss evolves throughout training, providing information about its ability to converge and effectiveness in generalizing on previously unknown data.

5.2 Discussion

Especially contrasted with existing systems, the proposed work provides a significant improvement in proactive maintenance oversight for Zigbee-enabled smart home networks. The proposed methodology, which employs revolutionary machine learning methodologies such as Firefly Optimization and XGBoost, offers several benefits over traditional approaches. First and foremost, compared to conventional decision trees and random forest algorithms, the addition of XGBoost enables the building of a robust ensemble model that can manage complicated linkages within the data and give more exact fault predictions [25]. This brings down deferral and gear disappointment costs by working on the consistency of administration intercessions. Second, the prescient model is improved for execution using Firefly Enhancement for hyperparameter alteration, which works on the prescient model's ability to sum up already obscure information and acclimate to changing ecological conditions in smart home organizations. As a result, the maintenance strategy can better adapt to changing user requirements and system complexity. Furthermore, the proposed procedure handles inadequacies of current frameworks, including their insufficiency to oversee convoluted highlight collaborations, loud information, and lacking hyperparameter settings. The proposed strategy works on the overall steadfastness and adequacy of support techniques in Zigbee-empowered brilliant home organizations by conquering these obstructions. However, the suggested method has limitations similar to those of any other strategy. These incorporate the requirement for extensive figuring resources and data handling abilities, as well as customary model assessment and improvement to guarantee ideal proficiency. The reliability of fault labelling and authentic facts, in addition to the quality and availability of the data, may have an impact on the method's performance. Innovative feature engineering approaches, incorporating more optimization techniques, and utilizing current information streamed facilities to provide anticipatory repair actions based on dynamic system circumstances are potential areas for improvement for future research. Moreover, thorough field checks and testing examinations in functionally smart home circumstances could show the recommended strategy's achievability.

6 Conclusion and Future Scope

The proposed study for intended performance enhancement in Zigbee-enabled smart home networks is a unique technique that employs powerful machine learning algorithms involving XGBoost and Firefly Optimization. The technique employs these methods to improve fault prediction accuracy, overcome system restrictions, and improve the dependability and effectiveness of maintenance operations. The effective implementation of XGBoost enables the development of an efficient ensemble model designed for managing complicated data connections, resulting in more exact fault predictions than earlier methodologies. Furthermore, Firefly Optimization improves model reliability by modifying hyperparameters, allowing you to adjust environmental circumstances and system complexity. The proposed study improves the technique of predictive maintenance by providing an exhaustive approach adapted to the specific challenges found in Zigbee-enabled smart home networks. The strategy addresses basic problems in previous systems by efficiently dealing with noisy data, complicated feature interactions, and inadequate hyperparameters, hence improving overall efficacy and dependability. Future research will focus on further in-depth evaluation and refining of machine learning approaches, such as experimenting with innovative feature engineering procedures and integrating new optimization methods to improve anticipated accuracy. Furthermore, including rapid data transfer technologies and undertaking large-scale field testing on genuine issues in smart home scenarios might give crucial insights into the proposed methodology's practical implementation and usefulness. Furthermore, looking into the methodology's adaption and transfer to other IoT-enabled technologies than smart homes might increase its relevance and impact.

Author contributions Franciskus Antonius Alijoyo and Rahul Pradhan, contributed on Conceptualization of introduction and existing approaches.Shaik Shakeel Ahamad contributed on the overall supervision. Vuda Sreenivasa Rao, Sanjiv Rao Godla worked on the results and discussion.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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Dr. Franciskus Antonius who is also known as Dr. Franciskus Antonius Alijoyo is the founder and principal of Center for Risk Management and Sustainability Indonesia (https://crmsindonesia.org). He is also senior lecturer at Parahyangan Catholic University, Bandung - Indonesia, and School of Business and Information Technology STMIK LIKMI Bandung - Indonesia. He has been active in academic world as well as practicing professional and board member for more than 30 years.

Dr. Rahul Pradhan is an esteemed technocrat, he imparts knowledge in the field of Computer Engineering and its Applications. A seasoned educator, Dr. Pradhan has many years of experience in teaching and research, specializing in information retrieval, natural language processing, and computer vision. His academic prowess is further highlighted by his thrice qualification in the IIT-GATE in Computer Science. Dr. Pradhan's scholarly output includes 8 international journal papers and 7 conference presentations, alongside supervising 26 undergraduate projects. An active member of professional bodies like IEEE, ACM, and CSI, Dr. Pradhan continues to contribute to the field of computer science through his research, teaching, and mentorship, making him a valued member of the Indian Academia.

Dr.Nalini Neelamegam is an Assistant Professor in the Department of Electronics and Communication Engineering at Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai. She is a dynamic individual who is passionate about research, learning, striving to enhance skills with a strong academic background. Currently her research areas include Image Processing, Internet of Things, VLSI Design, Machine Learning and Artificial Intelligence. She has more than 15 years of teaching experience and her research findings have been published in Scopus/IEEE conferences/SCIE Journals. She has attended and presented in many international conferences.

Dr. Shaik Shakeel Ahamad is currently working as an Associate Professor in CCIS, Majmaah University, Kingdom of Saudi Arabia. He holds a Ph.D. in Computer Science (cyber security) from the University of Hyderabad and IDRBT (Institute for Development and Research in Banking Technology), Hyderabad, India, in the realm of secure mobile payments protocols and formal verification. He has published more than 45 research papers in reputed International journals / Proceedings indexed by ISI, Scopus, ACM Digital Library, DBLP, and IEEE Digital Library. His research interests include cloud-based mobile commerce, secure mobile Payment frameworks, Block chain technology, Machine Learning, Deep Learning, Application Security, secure smart grids, and security and privacy in healthcare 4.0 and Smart Grids. He is serving as a Review Committee Member in many ISI indexed journals. He is currently working as an Associate Editor for the International Journal of Security & Privacy in Pervasive Computing (IJSPPC) https://www.igiglobal.com/journal/international-journal-security-privacy-pervasive/224361. He is a CEI (Certified EC Council Instructor), ECSA (EC-Council Certified Security Analyst), CHFI (Computer Hacking Forensic Investigator), Certified Threat Intelligence Analyst (CTIA), and Certified Application Security Engineer (CASE) – Java. He is a member of the IEEE, Association for Computing Machinery (ACM), ISACA, and OWASP (Open Web Application Security Project). He is serving as an External Expert Member (for Computer Science & Engineering (CSE) and Computer Applications) in Board of Studies (BoS) at School of Technology, Woxsen University, Hyderabad, INDIA. His contact details are ahamadss786@gmail.com & s.ahamad@mu.edu.sa

Dr. Vuda Sreenivasa Rao Dr. Vuda Sreenivasa Rao is an Associate Professor in the Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation (KL University),Vaddeswaram, AP, INDIA. He is a researcher with over 22 years of experience in the area of Data and Network Security, Attack Detection and Prevention, Security for Internet of Things, Sentiment Analysis, Medical Machine Learning, Disease Prediction, Object Detection with Deep Learning.

Dr. G. Sanjiv Rao obtained his M.Tech in computer science technology and MSc in computer science from Andhra University, AP, India in 2002 and 2005, respectively. He completed his Ph.D in computer science in 2015 at Andhra University in Vishakhapatnam, India. He currently holds the position of HOD and Professor in the Department of AI and Data Science at Aditya College of Engineering and Technology in Andhra Pradesh, India. He serves as the principal investigator for both internal and external research grants. His areas of interest include machine learning, cyber security, and WSNs.

Authors and Affiliations

Franciskus Antonius Alijoyo[1,2] · Rahul Pradhan[3] · N. Nalini[4] · Shaik Shakeel Ahamad[5] · Vuda Sreenivasa Rao[6] · Sanjiv Rao Godla[7]

✉ Franciskus Antonius Alijoyo
franciskus.antonius.alijoyo63@gmail.com

Rahul Pradhan
rahul.pradhan@gla.ac.in

N. Nalini
nalinineela07@gmail.com

Shaik Shakeel Ahamad
s.ahamad@mu.edu.sa

Vuda Sreenivasa Rao
vsreenivasarao@kluniversity.in

Sanjiv Rao Godla
sanjiv_gsr@yahoo.com

1 Center for Risk Management and Sustainability, Bandung, Indonesia

2 School of Business and Information Technology, STMIK LIKMI, Bandung, Indonesia

3 GLA University, Mathura, India

4 Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India

5 Department of Information Technology, College of Computer and Information Sciences, Majmaah University, Al Majma'ah, Kingdom of Saudi Arabia

6 Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India

7 Department of CSE(Artificial Intelligence and Machine Learning), Aditya College of Engineering and Technology, Surampalem, Andhra Pradesh, India