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Unveiling critical features for failure prediction in green internet of things applications

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ABSTRACT

The rapid growth of the green internet of things (GIoT) in recent years signifies a transformative shift in internet of things (IoT) solution development. This evolution is driven by technological advancements, heightened environmental awareness, and a global imperative to combat climate change. Ensuring the reliability of GIoT applications is crucial for their success. This study identifies critical features for predicting IoT device failures, enabling early detection and intervention. Using datasets from industry, energy, and agriculture sectors, we employ a feature selection strategy to analyze extensive data from diverse GIoT deployments. Our analysis identifies significant features and integrates key insights from existing literature. Our findings support enhanced predictive maintenance strategies, reduced downtime, and improved overall performance of sustainable IoT solutions.

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1. INTRODUCTION

In recent years, the internet of things (IoT) has seen substantial growth and integration across various facets of daily life [1]. As IoT continues to expand into numerous industries, the reliability and performance of IoT devices have become increasingly crucial. The IoT concept aims to use microcontrollers, transceivers, and protocol stacks for connectivity and combine everyday objects with the internet. By connecting everyday objects and devices to the digital world, the IoT has an extensive number of uses in daily life, from precision agriculture that optimizes farming practices to industrial IoT that revolutionizes manufacturing and production processes. IoT has created an interconnected network of smart devices, embedded sensors, and cloud computing, revolutionizing a variety of industries, including smart traffic [2], [3], healthcare [4], [5], agriculture [6], [7], and Industry 4.0. The IoT assists the current energy sector [8]. The integration of IoT technology with green energy applications marks a transformative leap toward a more sustainable future of renewable energy sources [9]. IoT technology facilitates connecting all the components of energy production and consumption, getting insight into the processes, and giving actual control at every stage of the energy flow, from exploitation to delivery to end users.

Predicting failures in green internet of things (GioT) application offers several advantages. First, it enhances system resilience by enabling rapid responses to potential disruptions, ensuring continuous operation in critical applications like smart grids, environmental monitoring, and healthcare systems, where downtime can have severe consequences. Early intervention improves system stability, allowing IoT infrastructure to recover quickly from potential failures. Secondly, it facilitates proactive maintenance strategies, reducing energy consumption and preventing unnecessary downtime [10]. Additionally, failure prediction extends the lifecycle of IoT devices, decreasing the need for frequent replacements and supporting sustainability efforts. By ascertaining key factors contributing to failures, researchers can further optimize design and manufacturing processes, resulting in more durable and efficient IoT solutions.

This study has been structured into six sections. Section 1 is the introductory phase, which presents the evolution of IoT and addresses the associated challenges. Section 2, sheds light on the background of IoT and GIoT. In section 3, the focus has been only on the literature review related to the green energy field. Section 4 highlights the challenges and techniques involved in feature selection for optimizing energy efficiency and resource consumption in GIoT. Results, challenges, and future research directions of the modern day have been discussed in section 5. Section 6 is the concluding portion of the research article. The articles have been extracted based on the highest number of citations over the past few years.

2. BACKGROUND

2.1. Internet of things architecture and components

The IoT is a global network infrastructure consisting of various connected devices that rely on sensors. It operates through a four-step architecture, as illustrated in Figure 1. Each stage in this process is interconnected, enabling data captured or processed at one stage to provide value to the next [5].

The following is a simplified representation of a typical IoT workflow. End devices: this phase involves the deployment of IoT devices or sensors at various locations to collect data from the physical environment. These devices consist of sensors, actuators, cameras, or other hardware that gather relevant data. They are responsible for collecting and transmitting data to the following phase.

Data preprocessing: the data collected by IoT devices is preprocessed before being effectively analyzed. This step includes data cleaning, filtering, and normalization to improve data reliability and accuracy. The data is modified or improved to render it suitable for analysis. Sensors or other devices frequently send back analog data, which need to be integrated and converted to digital format for further processing.

Data storage: after preprocessing, the combined and digitalized data needs to be properly stored in an appropriate repository for further analysis. This phase involves selecting a suitable storage solution, such as databases or data lakes while considering scalability, and data reliability. Additionally, the standardized data is transferred to the selected data center or cloud infrastructure for effective and secure storage.

Data analysis: in this stage, a variety of approaches are applied to the stored IoT data to extract relevant insights and knowledge. The data is examined for patterns, trends, correlations, and anomalies applying techniques including statistical analysis, data mining, artificial intelligence, and machine learning. The objective is to generate practical understandings to promote informed decisions.

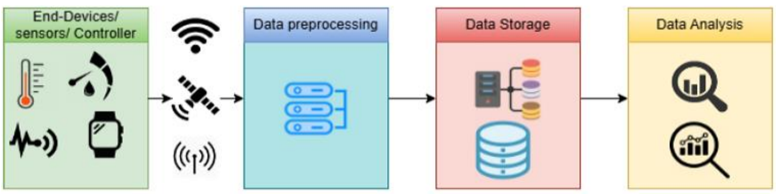

Figure 1. The four phases of IoT solutions

2.2. Green internet of things applications

GIoT applications have extensive effects across several areas, significantly advancing sustainability and efficiency. In energy management, Farhan *et al.* [11] have examined energy efficiency strategies and electric power systems for GIoT networks, highlighting the importance of sustainable practices. In smart agriculture, IoT devices can optimize agricultural practices, increase crop yields, and reduce environmental impact [12], [13]. In waste management, IoT technologies, such as smart bins equipped with sensors and solar power [14], promote environmentally friendly practices. Mohammadi *et al.* [15] state that a holistic approach integrates waste collection and sorting, reducing costs and minimizing social and environmental impacts. GIoT also enhances sustainable transportation by implementing technologies that reduce emissions and improve efficiency. Furthermore, environmental monitoring leverages IoT devices to provide real-time data for managing and protecting natural resources, as shown in studies [16]. These applications underscore the transformative potential of GIoT in fostering sustainable development.

3. RELATED WORK

The number of survey papers on GIoT that have attracted attention in recent years has increased. Alsharif *et al*. [17] advocates for the adoption of eco-friendly IoT solutions by thoroughly exploring energy-efficient practices and strategies which presents four principles/frameworks to achieve that vision by tackling the energy efficiency issues related to hardware such as machine-to-machine communication, radiofrequency identification, microcontroller units, wireless sensor networks, integrated circuits, embedded systems, and processors. The objective is to advance sustainable and energy-efficient IoT technologies, contributing to the next generation of eco-friendly implementations. Albreem *et al*. [18] examined effective behavioral change models to raise awareness about energy conservation among IoT users and service providers. This article delves into the key elements driving the development of the GIoTs, emphasizing energy efficiency hardware design, data-center strategies, and software-based data traffic management. Almalki *et al*. [19] are motivated by pursuing a sustainable smart world and delves into various technologies and considerations related to GIoTs to reduce energy consumption. The study systematically examines key green information and communication technologies (ICTs), including green radio frequency identification, green wireless sensor networks, green cloud computing, green machine-to-machine, and green data centers, while distilling general principles for green ICT. Varjovi and Babaie [20] examines the necessary measures to implement GIoT across various levels, including hardware, software, communication, and network architecture. Along with highlighting the significance of GIoT for environmental preservation, it also examines the prospects, difficulties, and uses of this technology. Leading IT organizations' business models are examined, and unresolved problems including standardization, technical difficulties, security, and innovations are examined to inform future studies. In order to lower energy usage and CO2 emissions, the study emphasizes the necessity of solutions at every stage of the GIoT life cycle, from design and production to use and recycling.

4. METHODOLOGY

This study provides a comprehensive approach to addressing IoT-based predictive maintenance challenges. The workflow focuses on the problem of predicting IoT device failures and extracting a list of essential features. Figure 2 illustrates the proposed methodology comprises three essential steps. Each step is elaborated in more detail as follows:

– Step 1: data collection. The first step involves collecting pertinent data from IoT devices, such as sensor readings, device logs, and historical maintenance records. This data serves as the foundation for building accurate predictive models. Preprocessing techniques are then applied to clean the data, handle missing values, and normalize the features, ensuring the data is suitable for analysis. By actively monitoring and analyzing this data, patterns, and anomalies can be detected, enabling the prediction of potential failures or malfunctions in IoT systems.
– Step 2: domains extraction. In IoT failure prediction, it is essential to identify and analyze the relevant domains or areas of focus within an IoT system that are prone to failures or malfunctions. Understanding the specific domains affected by failures makes it possible to develop more targeted and accurate failure prediction models. This step involves conducting domain-specific analysis and identifying the key factors or variables contributing to each domain's failures.
– Step 3: feature selection. In this step, we select and extract the dataset's most relevant and informative features. Feature selection methods, such as principal component analysis (PCA) and correlation analysis, are applied to identify the most influential features that significantly contribute to failure prediction. By focusing on the most important features, we can optimize the predictive models and enhance the accuracy of failure predictions.

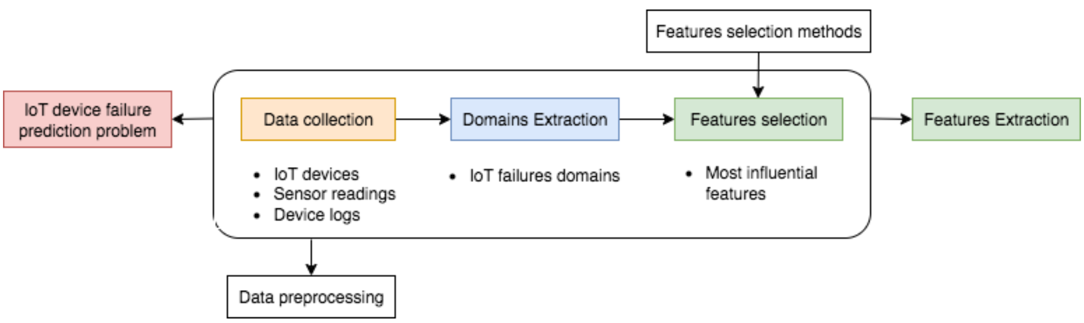

Figure 2. IoT-based predictive maintenance workflow

4.1. Data collection

Data collection provides a pivotal role in predicting IoT device failures. Several e-resources were identified, as presented in Table 1. Kaggle and IEEE DataPort emerged as the primary repositories employed in this research, as illustrated in Figure 3. Targeted keywords were used across multiple domains to facilitate comprehensive data collection. Examples of these keywords include "IoT failure in {domain}" and "monitoring IoT device failures".

Table 1. List of e-resources for dataset discovery

No.	E-resources	Content
1	https://www.kaggle.com/	Databases
2	https://ieee-dataport.org/subscribe	
3	https://zenodo.org/	
4	https://archive.ics.uci.edu/ml/datasets.php	
5	https://github.com/	

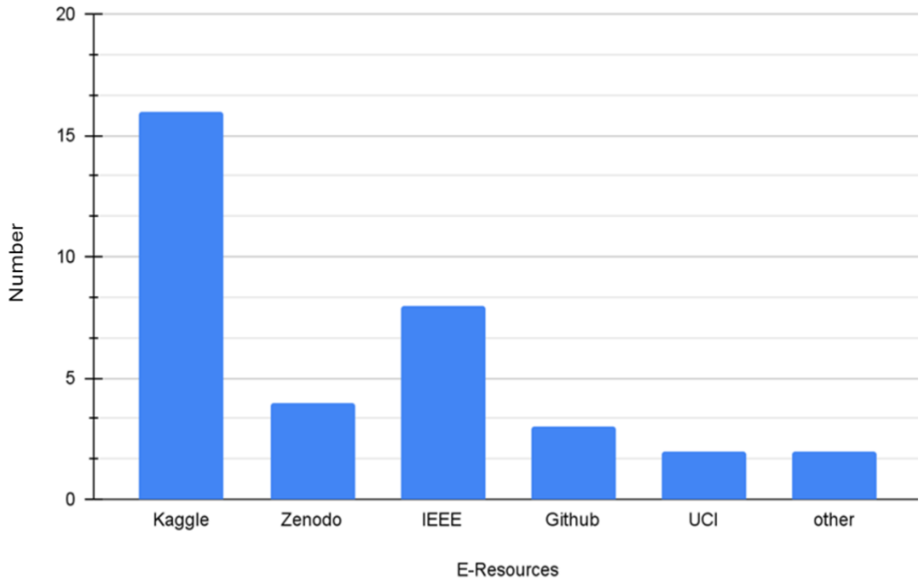

Figure 3. Distribution of e-resources used in the study, highlighting Kaggle and IEEE DataPort as primary sources

The size of the dataset has a significant impact on the results of the implemented models. Thus, in this study, we considered the datasets' sizes an important key feature. The dataset sizes varied significantly, ranging from 6.11 kB to 6 GB. Figure 3 illustrates the use of Kaggle and IEEE DataPort as primary sources, highlighting their importance in providing relevant and high-quality datasets for IoT failure prediction research, followed by Zenodo, GitHub, UCI, and other similar sources. These sources offer a wide range of datasets encompassing different domains, which enables us to examine failure patterns, identify key features, and develop accurate predictive models across diverse IoT applications.

4.2. Domaine extraction

The exploration of IoT across various applications has revealed significant opportunities to develop advanced systems in diverse domains. Predicting IoT device failures offers considerable benefits in these areas. Figure 4 illustrates the distribution of datasets used for IoT failure prediction in various domain applications. A total of 32 datasets, 19 from the industry sector, 5 from agriculture, and 6 from energy. However, some data contain unclear labels and abbreviations, which can lead to confusing the context and understanding of the dataset. A rigorous data preprocessing approach will be put in place to overcome these challenges. These include the elimination of confusing datasets, maintaining well-defined features, and renaming labels to enhance the dataset's comprehensibility. In the next section, a feature selection strategy was applied to identify the key features of this study.

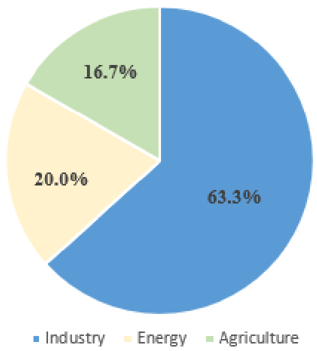

Figure 4. The distribution of collection data by domain

4.3. Feature selection strategy

In this section, we explore a range of feature selection methods, each adapted to the specific approach for identifying essential features. Feature selection plays a pivotal role in identifying the key contributors to IoT device failures. The objectives are to understand the data, reduce computational demands, mitigate the effects of the curse of dimensionality, and enhance the performance of predictive models [21]. Feature selection aims to choose a subset of relevant variables from the input data. This process involves minimizing the influence of noise or irrelevant variables while ensuring that the selected features contribute to accurate predictions and optimized computational efficiency. Effective feature selection can significantly improve model performance, reduce overfitting, and lower the computational cost associated with processing large datasets. Feature selection methods are generally classified into two categories: supervised and unsupervised methods, as shown in Figure 5.

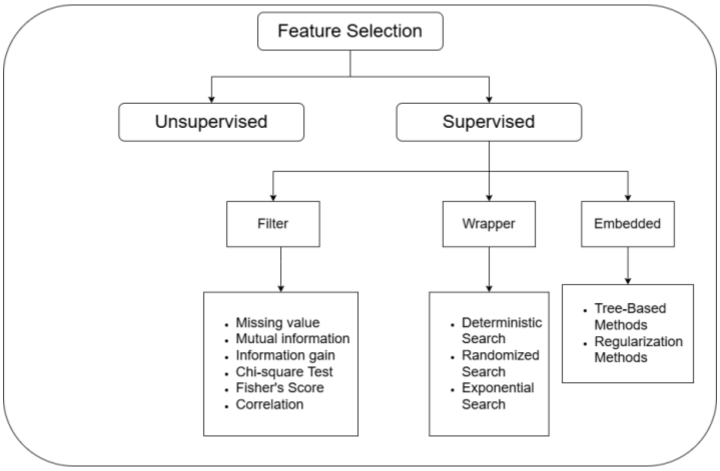

Figure 5. Overview of feature selection techniques

Supervised feature selection targets classification tasks by leveraging the relevance or correlation between features and class labels. The objective is to identify an optimal subset of features that enhances classification accuracy. Various supervised techniques have been developed for that purpose [22]. Filter methods are preprocessing processes for evaluating features, selecting those with high relevance scores based on mutual information and correlation measurements [23]. On the other hand, wrapper methods apply sequential or heuristic search techniques to identify the feature subset that maximizes performance through embedding the predictor within a search algorithm. Embedded methods include feature selection directly within the training process, eliminating the need for splitting data into separate training and testing sets. Additionally, hybrid approaches and ensemble techniques combine filter and wrapper models, typically involving two stages: initially reducing the feature space using the filter, and then employing the wrapper to determine the most effective subset among the remaining features [21].

Other approaches highlight the important features of lacking dataset labels for unsupervised learning. Clustering is a typical approach that groups similar data points. Clustering techniques, such as hierarchical clustering and density-based clustering, organize data into clusters based on their proximity, revealing underlying patterns without predefined classifications [24]. By applying these advanced feature selection methods, we aim to enhance the accuracy and reliability of predictive models, ultimately improving the effectiveness of IoT device failure predictions. In this study, the dataset goes through several stages. After the preprocessing phase, exploratory data analysis (EDA) is applied. EDA provides valuable details about the dataset, exposing distribution patterns and correlations between important characteristics. EDA serves as a crucial guide for the next stages, assisting in data selection and facilitating the execution of machine learning tasks [25]. After preprocessing, a feature selection strategy is applied to create a representative subset of features critical for predictive modeling with AI methods. Performing EDA prior to feature selection is essential for understanding dataset characteristics and identifying potential relationships between input features and target variables [26]. This comprehensive approach ensures the selection of meaningful features for effective modeling.

The feature selection strategy begins with an EDA to assess the characteristics and correlations among the original features. This is followed by the implementation of advanced selection techniques, including feature importance, information gain, Chi-square test, Fisher's score, mutual information gain, recursive feature elimination, and PCA. These methods are used for supervised learning, else other feature selection methods are adopted for unsupervised learning. Variance threshold, mean absolute difference (MAD), clustering k-means, hierarchical clustering, density-based clustering, PAM, Gaussian mixture model (GMM), and self-organized maps (SOM) were implemented to eliminate the irrelevant original features. The study is implemented in Python along with the required libraries, such as scikit-learn, Matplotlib, and Skfeature. The feature selection strategy eliminates irrelevant original features, revealing deeper insights within the remaining dataset.

5. RESULTS AND DISCUSSION

5.1. Results of feature selection strategy

A rigorous feature selection strategy was implemented to identify critical variables in our research. EDA and other methods were employed to select important features. Table 2 presents an overview of the results, highlighting the contributions and application domains of each selected dataset. There is no unified feature selection strategy that can select important features in the application, we need to select the most appropriate methods among a range of different methods to achieve the best performance. Features selection is an important step in failure prediction problems, especially in GIoT applications. By applying the feature selection strategy outlined in the previous section, the number of selected features was reduced by more than half. Thus, combining these selected features can help generate new, original features for training models in future work.

Table 2. Datasets features selection

ID	Contribution	Application	Features selection results
1	Predictive maintenance dataset	Industry	Torque, tool wear, rotation speed, air temperature, process temperature
2	Machine failure dataset		Leakage, risk_MM, max_temp, parameter1_speed, electricity, evaporation, min_temp
3	Predictive maintenance using Microsoft case study		Pressure, rotate, voltage, vibration
4	Elevator predictive maintenance dataset		Vibration, revolutions
5	Preventive to predictive maintenance		Dust_feed, differential_pressure, time
6	AnoML-IoT		Light, humidity, loudness, temperature
7	Predicting machine failures		Temperature, humidity, hours since previous failure, date.day-of-month, date.day-of-week, date. month, date. hour.
8	Distributed transformer monitoring	Energy	Oil temperature indicator, winding temperature indicator, ambient temperature indicator, oil level indicator, oil temperature indicator alarm, oil temperature indicator trip, magnetic oil gauge indicator, voltage
9	MetroPT: a benchmark dataset for predictive maintenance		gpsSpeed, gpsLat, gpsLong, Tp2, oil_temperature, flow meter, motor_current, gpsQuality, H1, Tp3, DV_pressure, COMP, caudal_impulses, MPG
10	Smart home dataset with weather information		Wind Bearing, dew point, apparent temperature, temperature, well, pressure, wind speed, humidity, house overall, solar, visibility, furnace, wine cellar, precipIntensity, precipProbability
11	Real-time pond water dataset for fish framing	Agriculture	pH, temperature
12	Smart agricultural production optimizing engine		Potassium, rainfall, temperature, humidity, phosphorus, nitrogen, pH
13	Intelligent irrigation system		Humidity, temperature, watering
14	Sensor-based aquaponics		Temperature, turbidity, dissolved oxygen, pH, ammonia, nitrate

5.2. Critical features for failure prediction

The primary goal of this study is to identify the critical features for predicting failures in GIoT applications. Table 3 provides an overview of the extracted features from various research articles, including their contributions and domains of application. An analysis of the data presented in Tables 2 and 3, complemented by Figures 6 and 7, reveals significant patterns in feature usage across different datasets.

Table 3. Key features identified in the literature and their domains of application

References	Contribution	Application	Sensors/actuators	Features selection results
[27]	Prediction of machine failure in Industry	Industry	-	Voltage, pressure, vibration, rotation, machine age, error type, number of components, model type and failure
[28]	Predictive maintenance analytics of autoclave sterilizer		-	Temperature, vibration, two current
[29]	Rail transit vehicles		-	vibration
[30]	MEP components HVAC systems		Temperature sensor, pressure sensor, flow rate sensor	Sensor name, sensor id, sensor value, sensor type
[31]	Industrial equipment monitoring: electrical motors		ADXL345, ACS712, temperature sensor, MLX90614 Infra-red thermometer, SHT21 digital humidity and temperature sensor	Vibration measurement, temperature, voltage
[32]	Wind turbines	Energy	-	Wind speed, power output, oil temperature, bearing temperature
[33]	Fault detection and power prediction of photovoltaic plants		Temperature sensor, humidity sensor, irradiance sensor, voltage sensor, current sensor	Temperature, irradiance, power, voltage, humidity, current
[34]	IoT smart home		Temperature sensors, humidity, leak, water, smoke, air sensor, light sensors, dry contact sensors, smart plugs, current transformers, AC/DC voltage sensors, power synching sensors, smart home monitoring kits	-
[35]	Smart framing	Agriculture	CO2 sensor, UV sensor, luminance sensor, soil sensor, barometric pressure sensor, moisture, temperature, electrical conductivity (EC), pH sensors	-
[36]	Smart framing: calibrationTalk		Soil sensors, temperature, EC, moisture sensors, humidity sensor, nitrogen, phosphorus, potassium	-
[37]	IoT-based monitoring system: aeroponics greenhouse		Temperature: MLX90614(TS1ca), humidity: HTU21D(HS1c), humidity of the environment: HTU21D(HS1a), luminous sensor: BH1750(IS1a), webcam: LC4, IP camera UC4	Temperature, environmental temperature relative humidity, luminosity, pH level, EC (electrical conductivity), level and nutrient solution temperature, RGB and thermographic images
[38]	Smart framing: greenhouse		Temperature/humidity: E+E elektronik EE160, electrical connectivity: B&C electronics 2731312-31/3-017T, pH: B&C electronics SZ 1093, level controller: Omron K8AK-LS1, liquid counter: ARAD SF 15, flow meter: Gems FT110 G3/8, solar radiation: Apogee, Instruments Inc. SP110	Temperature, humidity, electrical connectivity, pH, level controller, liquid counter, flow meter, solar radiation, CO2, nitrogen, sulphur, phosphorus, calcium, potassium, iron, copper, manganese, boron, zinc, molybdenum
[39]	Smart sensors in agriculture		Leaf sensor, temperature sensor, crop sensor, disease sensor, pest sensor, nutrient sensor, soil moisture sensor, acoustic-based sensor, electromagnetic sensors, electrochemical sensors: volatile organic compound sensor, humidity sensor, nutrient sensor, pesticide sensor, O3 sensor, NO2 sensor, light detection and ranging (LiDAR), optical sensors, field programmable gate array (FPGA) based sensors, Eddy covariance (EC) based sensors, Mechanical and mass flow sensors, flexible and wearable sensors, battery-free and self powered sensors	-

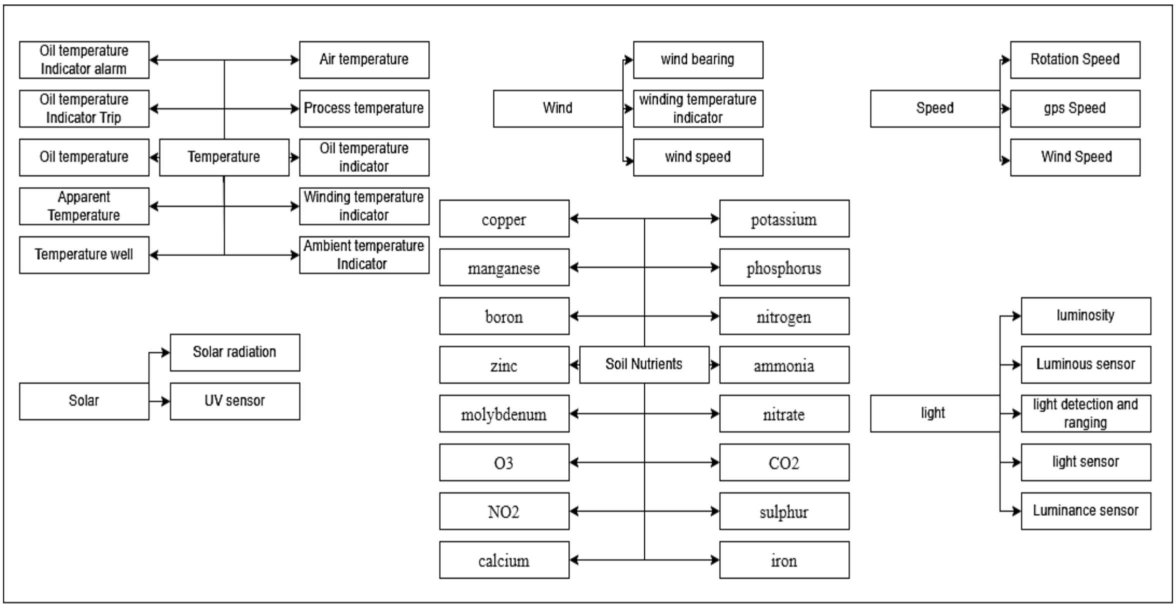

Figure 6. Study's key features variety

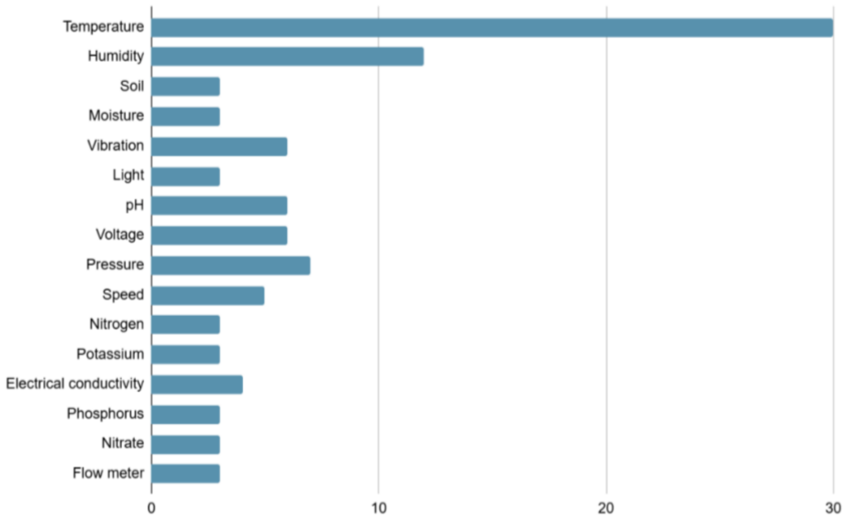

Figure 7. Study's features frequency

Figure 6 categorizes these features using standardized terms, highlighting their broad applications and variations. For example, the term "temperature" is consistently represented in various forms such as "oil temperature" and "air temperature", demonstrating its fundamental role in different contexts. Similarly, the term "Wind" appears in multiple forms, including "wind bearing", "wind speed", and "wind temperature indicator", indicating its importance in capturing diverse atmospheric conditions. The term "speed" also shows considerable variation, with instances such as "rotation speed", "GPS speed", and "wind speed", reflecting its application across different measurement scenarios. Additionally, "Light" is denoted by various descriptors including "luminosity", "luminous sensor", and "light sensor", while "soil nutrient" covers specific elements such as "zinc", "nitrogen", "CO2", and "sulphur". The term "solar" includes "solar radiation" and "UV sensor", highlighting its relevance to solar energy studies.

This analysis underscores the necessity for standardized feature terminology to improve data consistency and comparability. By aligning terminology across datasets, researchers can ensure more accurate and coherent data integration, facilitating better comparative analyses and enhancing the robustness of predictive models. This approach streamlines data processing and improves the reliability of insights derived from diverse research studies and application domains.

The high frequency of certain terms in this study strongly indicates their importance. This recurrence shows the significance of these features across various datasets and applications in predictive analysis. The frequency of the most cited terms from Tables 2 and 3 is shown in Figure 7. For instance, terminology such as “temperature”, “humidity”, “pressure”, “voltage”, “pH” and “vibration” appear frequently. With over thirty citations “temperature” is referenced, followed by “humidity” which indicates their importance in the datasets analyzed. The recurrence of these terminologies across multiple studies and datasets substantiates their indispensability, which are key indicators for monitoring and predicting IoT device performance.

6. CONCLUSION

The present study reviews the crucial features for predicting failures in GIoT applications in significant sectors, including agriculture, industry, and energy. A variety of datasets and research papers focus on these features' critical role in predictive maintenance. Features such as temperature, humidity, voltage, vibration, and pH are highlighted through a workflow process of data collection, domain extraction, and feature selection. In future work, we will focus on developing predictive models using the most crucial features within each domain. We aim to implement a robust model capable of predicting failures before they can occur, optimizing performance, and reducing downtime. This study will contribute to developing reliable and sustainable GIoT technologies, supporting environmental sustainability, and advancing the capabilities of IoT systems in various domains.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Author Mohammed Hassine was employed by the company Tisalabs Limited. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

INFORMED CONSENT

Not applicable.

ETHICAL APPROVAL

Not applicable.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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