https://doi.org/10.31449/inf.v49i8.6502 Informatica **49** (2025) 29-42 **29**

IoT-based Intelligent Power Supply Management Using Ensemble Learning for Seismic Observation Stations

Gao Qin[1,2,3], Meng Juan[1,2,3], Ma Hong Rui[1,2,3]
[1]China Institute of Disaster Prevention, Sanhe 065201, China
[2]Hebei Key Laboratory of Seismic Disaster Instrument and Monitoring Technology, Sanhe 065201, China
[3]Langfang Key Laboratory of Accurately-Controlled Active Seismic Source, Sanhe 065201, China
E-mail: LingliYao666@outlook.com

Keywords: iot-based intelligent power supply management system, operational continuity, power failures prediction, seismic observation stations, seismoguard ensemble classifier

Recieved: June 26, 2024

Seismic observation stations perform a vital part in monitoring and analyzing seismic activity for early warning and disaster preparedness. This paper investigates the integration of an IoT-based intelligent power supply management model to improve station reliability and effectiveness. Traditional systems often suffer from reliability issues and inadequate monitoring, impacting timely seismic data delivery during critical events. The study employs IoT sensors for real-time monitoring of voltage, current, battery status, and environmental conditions. Data are centralized for analysis, leveraging the SeismoGuard Ensemble classifier—a novel machine learning model combining Random Forest, SVM, and KNN models with a Logistic Regression meta-classifier. The novelty lies in its distinctive blend of Random Forest, SVM, KNN, and Logistic Regression improves predictive accuracy and robustness in power supply handling for seismic observation stations. This approach improves forecasting accuracy and robustness in preventing power failures, achieving high prediction measurements like accuracy (90%), precision (88%), recall (91%), and F1-score (89%). Implementation leads to enhanced data transmission throughput and packet delivery ratio, ensuring reduced downtime and increased resilience during seismic events. Integrating IoT technologies in power supply management offers substantial benefits, including enhanced reliability and operational continuity, vital for effective seismic monitoring and early warning systems.

Povzetek: Raziskava izboljšuje zanesljivost seizmoloških opazovalnic z uporabo IoT za spremljanje napajanja in napovedovanje okvar z algoritmom SeismoGuard Ensemble, ki združuje algoritme naključnih gozdov, SVM in KNN.

1 Introduction

Seismic observation stations are essential infrastructure used to observe and analyze seismic activity, playing a crucial role in providing early warnings and preparing for disasters [1]. These stations detect ground vibrations and seismic waves from earthquakes and volcanic activity, providing critical data for seismologists, emergency responders, and policymakers. However, the continuous operation of these stations relies heavily on reliable power supply management systems. Interruptions in power can severely disrupt real-time monitoring and data transmission during critical seismic events, underscoring the necessity for robust power management solutions [2].

Traditional power supply systems in seismic observation stations typically employ basic monitoring and control mechanisms [3]. These systems often rely on manual oversight and lack advanced monitoring capabilities, leading to inefficiencies and delayed responses to power disruptions. Moreover, their reactive maintenance approaches and limited scalability pose challenges in meeting the dynamic demands of seismic monitoring environments [4]. These shortcomings highlight the need for modernized, IoT-based intelligent power supply management systems.

The rise of the Internet of Things (IoT) offers transformative potential in enhancing power supply management in seismic observation stations [5]. IoT enables the integration of advanced sensors and communication devices to monitor critical parameters such as voltage, current, battery status, and environmental conditions in real time. By leveraging IoT capabilities, stations can implement proactive monitoring, predictive maintenance, and adaptive responses to optimize power supply operations and ensure uninterrupted functionality during seismic events.

An IoT-based intelligent power supply management system centralizes data from distributed sensors, facilitating comprehensive analysis and decision-making. Centralization enables operators to detect anomalies, predict potential failures, and implement preemptive measures to mitigate risks effectively. However, accurate classification and prediction of power failures remain pivotal challenges. Existing techniques often suffer from limited predictive accuracy and struggle with the variability and difficulty of seismic monitoring data.

To address these challenges, this paper introduces the SeismoGuard Ensemble classifier—a sophisticated machine-learning paradigm that blends the advantages of Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression meta-classifier through ensemble learning. This hybrid approach enhances prediction accuracy, robustness against outliers, and adaptability to dynamic environmental conditions in seismic observation stations. By integrating diverse learning strategies, the classifier improves forecasting precision and enables proactive management of power supply systems.

This paper aims to contribute by proposing and evaluating an IoT-based intelligent power supply management system integrated with the SeismoGuard Ensemble classifier for seismic observation stations. The study assesses the system's effectiveness in enhancing reliability, optimizing resource allocation, and improving operational continuity. The findings hold implications for disaster preparedness, infrastructure resilience enhancement, and early warning systems deployment in seismic-prone regions.

The organization of the paper is structured as follows: Section 2 investigates related work in IoT-based power supply management and classification techniques. Section 3 provides the methodology employed, including the strategy and implementation of the IoT-based power supply management system integrated with the SeismoGuard Ensemble classifier. Section 4 presents experimental results and discussions on the system's functionality in seismic monitoring scenarios. Section 5 summarizes crucial results, discusses constraints, and suggests upcoming investigations for seismic station power supply management.

2 Related work

The integration of IoT technologies with power supply management systems and seismic observation has been extensively explored in recent years. This section explores IoT applications in energy management and earthquake prediction, highlighting current strengths, limitations, and the call for advanced solutions.

Hossein Motlagh et al. [6] provide a comprehensive review of IoT applications in the sector of energy, emphasizing its role in enhancing energy efficacy, raising the proportion of energy from renewable sources, and lessening the effects on the environment. They discuss various IoT-based frameworks and their impact on energy systems, particularly within the environment of smart grids. The authors also investigate enabling technology like data evaluation systems and cloud computing, alongside challenges like privacy and security, proposing blockchain as a potential solution. Their survey offers valuable insights for policymakers and energy managers on optimizing energy systems through IoT integration.

Expanding on distributed energy systems, Sadeeq and Zeebaree [7] examine the role of distributed energy system (DES) architectures in managing renewable energy sources and addressing the volatility of energy prices. Their study highlights the importance of end-user participation in intelligent energy management and the provision of auxiliary services to support grid operators. By delivering robust planning, constraint control, and scheduling, distributed systems can enhance system reliability and demand response. Their literature and policy analysis underscores the need for effective energy management system aggregators to navigate the challenges and opportunities within smart grid technologies.

Pawar and Tarun Kumar [8] focus on an IoT-based Intelligent Smart Energy Management System (ISEMS) designed for the economical use of sustainable energy without limiting power consumption. Their proposed system employs planning ahead of time and precise power supply predictions using an SVM regression model based on PSO. This approach operates more accurately than other forecasting methods, demonstrating its effectiveness through various user-end configurations. The integration of IoT for monitoring enhances features that are important and comfortable for users, showcasing the potential of intelligent systems for managing energy in optimizing renewable energy use.

Ahmad and Zhang [9] explore the deployment of IoT in networks and systems for intelligent energy use, discussing its uses in transmission, energy production, incorporating renewable energy sources, load requirements management, and supply of energy. Their study highlights the advantages of IoT-enabled smart grids in terms of enhanced monitoring, control, and automation. They categorize IoT applications into business, smart energy systems, data transmission networks, and power generation, providing a detailed analysis of each area. The authors emphasize the significant growth in the IoT energy market and its potential to transform smart energy systems through innovative solutions.

In the realm of energy harvesting, Zeadally et al. [10] review design architectures for energy harvesting in IoT applications. They discuss various energy harvesting techniques and their suitability for IoT-based energy management systems. The study identifies key challenges in developing efficient energy harvesting solutions, such as ensuring continuous and reliable energy delivery. By leveraging sustainability assets that are either naturally or artificially attainable, IoT systems can reduce reliance on batteries and enhance sustainability, making them long-lasting and cost-effective.

Abdalzaher et al. [11] investigate the application of machine learning and IoT and seismic early alerting mechanisms for smart cities. Their research highlights the integration of IoT sensors with sophisticated ML techniques to improve the accuracy and timeliness of earthquake predictions. The proposed system employs IoT for real-time data collection and ML for interpretation of data, offering a robust framework for risk reduction and disaster handling. This combination of technologies enhances the system's capability to provide reliable early warnings, contributing to the safety and preparedness of urban populations.

Mia et al. [12] propose an IoT-integrated belief rule-based approach for earthquake prediction. Their system aggregates data from sensors monitoring animal behavior, and environmental, and chemical changes to predict earthquakes. The belief rule-based system uses knowledge representation criteria such as the degree of belief, rule weight, and attribute weight to analyze the data. Their results show that the belief rule-based system with IoT integration offers better prediction accuracy compared to expert and fuzzy-based systems, demonstrating its potential to enhance earthquake preparedness.

Falanga et al. [13] introduce a significantly improved IoT-focused framework for finding seismic events, applied to Volcanoes Vesuvius and Colima. Their framework utilizes semantic web technologies to encourage lexical and linguistic compatibility in IoT ecosystems, improving the quality of the data through ontology annotation. The system collects, processes, and stores seismic data in a knowledge base using the Volcano Event Ontology (VEO). The classification module detects different seismic events, providing timely and accurate information crucial for tracking volcano dynamics and responding to explosive crises.

Tehseen et al. [14] present a structure for earthquake forecasting using federated learning (FL), which addresses issues related to data privacy, transmission latency, and processing capacity. Their novel FL framework aggregates local data models to generate a global model, ensuring data security and heterogeneity. The proposed system demonstrates superior performance in earthquake prediction accuracy compared to traditional ML models. The FL framework is validated using regional seismic data, showing its potential to enhance earthquake early warning systems through improved efficiency and reliability.

Sharma et al. [15] discuss an IoT-based disaster management framework that leverages interconnected devices for real-time monitoring and response. Their study highlights the importance of IoT in catastrophe control, providing examples of promptly alert systems for the discovery of fire and earthquakes. The proposed framework enhances coordination among emergency response teams, improving situational awareness and disaster management effectiveness. By integrating IoT technologies, the framework aims to save the structures of smart cities and reduce the hazards of disasters. Table 1 shows the summary of Related Works on IoT and Seismic Observation Systems.

Table 1: Summary of related works on iot and seismic observation systems

Author/Year	**Techniques/Methods Used**	**Key Metrics**	**Limitations and Gaps**
Hossein Motlagh et al. [6]	IoT use cases in the energy sector, smart grids, data evaluation systems, blockchain	Energy effectiveness enhancement, renewable energy share	Confidentiality and safety concerns, lack of detailed execution tactics
Sadeeq and Zeebaree [7]	Distributed energy system (DES) architectures, planning, limitation handling	System reliability and responsiveness	Essential for effective energy management aggregators, constrained end-user engagement
Pawar and Tarun Kumar [8]	IoT-based Intelligent Smart Energy Management System (ISEMS), SVM regression, Particle Swarm Optimization	Improved prediction precision	Concentration on particular user configurations, generalizability problems
Ahmad and Zhang [9]	IoT in energy use networks, load management, smart grids	Enhanced monitoring and control	Lack of emphasis on incorporation difficulties, restricted concentration on real-time data

Zeadally et al. [10]	Energy harvesting methods for IoT use cases	Sustainability and economic viability	Difficulties in consistent energy provision, inadequate scalability
Abdalzaher et al. [11]	IoT sensors integrated with machine learning for seismic early warning systems.	Improved precision and timeliness of earthquake predictions	Incorporation intricacy of IoT with machine learning, real-world applicability
Mia et al. [12]	Belief rule-based methodology combined with IoT	Enhanced prediction accuracy	Need on various data sources, possible biases in animal behavior data
Falanga et al. [13]	IoT framework utilizing semantic web technologies for seismic event discovery	Improved data excellence and event classification	Restricted applicability to non-volcanic seismic events, data annotation problems
Tehseen et al. [14]	Federated learning for earthquake forecast	Improved accuracy in earthquake forecast	Data model consolidation intricacy, restricted dataset diversity
Sharma et al. [15]	IoT-based disaster management framework, real-time tracking and response	Enhanced situational awareness	Restricted to particular disaster situations, difficulties in emergency coordination

Despite the advancements in IoT-based energy management and earthquake prediction systems, existing techniques face several limitations. Many studies [6]-[15] report challenges such as inadequate predictive accuracy, sensitivity to environmental variations, and difficulties in handling large-scale data integration. Traditional machine learning models often struggle with the complexity and unpredictability of seismic data, resulting in suboptimal performance in real-world scenarios.

To tackle these challenges, this paper proposes the SeismoGuard Ensemble classifier, integrating Random Forest, SVM, KNN, and Logistic Regression. It aims to enhance prediction accuracy and adaptability in seismic observation systems using IoT-based power supply management.

3 Methodology

3.1 Research design

This study proposes the development and implementation of an IoT-based intelligent power supply management system designed to improve the reliability and effectiveness of seismic observation stations. The core of this approach is the SeismoGuard Ensemble classifier, an advanced machine learning model that integrates the predictive capabilities of Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) models through a stacking method, combined with a Logistic Regression meta-classifier. This innovative system aims to predict power failures, thereby mitigating downtime and ensuring continuous operation during critical seismic events.

The research design employs a mixed-methods approach, integrating quantitative data analysis with sophisticated machine-learning techniques. The design encompasses several key phases: gathering of data, preprocessing data, model development, system integration, and assessment of effectiveness. The quantitative aspect involves extensive data collection from various IoT sensors installed at seismic observation stations. These sensors monitor critical parameters such as voltage, current, battery status, and environmental conditions in real-time, providing a comprehensive dataset for analysis.

In the data collection phase, IoT sensors are strategically placed at seismic observation stations to ensure comprehensive monitoring. These sensors perpetually log data that is then transmitted to a centralized database for storage and analysis. The data preprocessing phase involves cleaning the gathered information to eliminate anomalies and noise, ensuring the dataset's quality and reliability. Statistical techniques are applied to understand data distributions, trends, and relationships among variables, forming the basis for developing the predictive model.

The heart of the proposed work lies in the development of the SeismoGuard Ensemble classifier. This classifier combines multiple machine learning algorithms to improve prediction precision and resilience. The chosen models, Random Forest, SVM, and KNN, are known for their strengths in classification activities and their capacity to manage difficult, high-dimensional data. By stacking these models and integrating them with a Logistic Regression meta-classifier, their combined predictive power is leveraged. The training process involves dividing the dataset into training and testing subsets, employing cross-checking, and performing a grid search for improvement of hyperparameters to ensure the model's robustness and accuracy.

Once developed, the SeismoGuard Ensemble classifier is integrated into the IoT-based power supply management system. The system architecture includes IoT sensors, data acquisition modules, and centralized processing units. This integration enables tracking power supply aspects in real-time and environmental conditions, allowing for the detection of anomalies and potential failures. The predictive analytics powered by the SeismoGuard Ensemble classifier analyze the real-time data to predict power failures before they occur, enabling proactive management and mitigation strategies.

The evaluation framework for the proposed system includes deploying it at selected seismic observation stations to test its functionality and performance under real-world conditions. Key performance metrics like accuracy, precision, recall, F1-score, data transmission throughput, and packet delivery ratio are used to assess the system's effectiveness.

3.2 System architecture

The proposed IoT-based intelligent power supply management system comprises several key components (Figure 1):

IoT sensors and devices

The system incorporates IoT sensors and devices strategically deployed at seismic observation stations. These devices continuously monitor various parameters in real-time, including voltage, current, battery status, and environmental circumstances, including temperature and humidity. The information gathered by these sensors is vital for assessing the power supply status and detecting anomalies that might indicate potential failures.

The IoT sensors were calibrated according to manufacturer specifications to guarantee precise readings of voltage, current, and ecological conditions like temperature and humidity. Calibration entailed comparing sensor readings to preset values under controlled settings to adjust any deviations. Sensor placement at seismic monitoring locations was meticulously designed to maximize data quality while minimizing interference from environmental obstacles or electrical noise. To avoid sensor failure, redundant sensors were placed in important regions, and periodic service checks were performed to evaluate sensor health and recalibrate as needed.

Data acquisition module

The Data Acquisition Module plays a pivotal role in collecting data generated by the IoT sensors. Serving as an intermediary, it ensures accurate and efficient transmission of data to the next stage of the system. Maintaining data integrity and timely transfer to the centralized server is essential for enabling real-time monitoring and analysis.

Centralized data processing unit

Utilizing cloud computing resources, the Centralized Data Processing Unit manages the data collected from various seismic observation stations. It performs critical functions such as storing enormous volumes of data, analyzing it to recognize trends and patterns, and processing it to extract meaningful insights. Cloud computing capabilities facilitate scalability, flexibility, and efficient handling of large datasets, essential for robust system performance.

SeismoGuard ensemble classifier

The SeismoGuard Ensemble Classifier is a sophisticated machine-learning model specifically designed for the system. It analyzes processed data to predict potential power failures with high accuracy. Leveraging advanced machine learning techniques, the classifier identifies subtle indicators of power supply issues that may be overlooked by traditional methods. Its predictive capabilities enable proactive management of the power supply, reducing the risk of unexpected outages and enhancing overall system reliability.

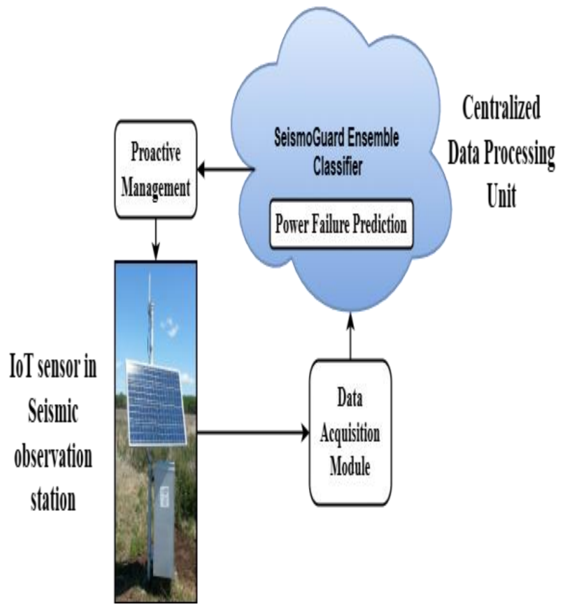

Figure 1: IoT-based intelligent power supply management system in seismic observation stations

Overall, the system architecture integrates IoT sensors, data acquisition modules, centralized data processing, and advanced machine learning to create an intelligent power supply management system. This holistic approach ensures real-time monitoring, efficient data handling, and accurate predictions, enhancing the reliability and resilience of power supply systems at seismic observation stations.

3.3 Data collection

Data collection within the system was systematically carried out across multiple seismic observation stations equipped with IoT sensors. These sensors were strategically deployed to ensure comprehensive monitoring of essential parameters critical for evaluating the health of the power supply infrastructure.

At each seismic observation station, IoT sensors operated autonomously, continuously monitoring a range of parameters including voltage, current levels, battery health metrics, as well as ambient temperature and humidity conditions. This continuous monitoring provided real-time insights into the operational status of the power supply infrastructure, allowing for early detection of potential issues or anomalies.

The gathered information underwent thorough validation and preprocessing procedures to verify accuracy and reliability. Validation processes were implemented to determine and deal with any outliers or inconsistencies in the data, thereby enhancing the quality of the datasets used for subsequent analysis.

Once validated, the processed data were securely transmitted to the central server using reliable communication protocols. These protocols were chosen for their ability to guarantee effective and safe data transfer, safeguarding the integrity and confidentiality of the transmitted information throughout its journey to the central server.

By leveraging IoT sensors and robust data transmission protocols, the system facilitated continuous and accurate data collection from multiple observation points. This robust data collection framework served as a crucial foundation for ongoing analysis and decision-making processes within the intelligent power supply management system, supporting proactive maintenance and operational efficiency.

The structure of the collected dataset includes various parameters such as timestamp, voltage, current, battery status, temperature, humidity, and power failure events. The sample dataset is structured as shown in Table 2.

Table 2: Sample dataset structure

Timestamp	Voltage (V)	Current (A)	Battery Status	Temperature (°C)	Humidity (%)	Power Failure (Binary, 0/1)
2024-06-21 08:00:00	220	15	80%	25	50	0
2024-06-21 08:15:00	218	16	78%	26	52	0
2024-06-21 08:30:00	216	14	75%	27	54	0
2024-06-21 08:45:00	215	13	73%	28	55	0
2024-06-21 09:00:00	50	5	10%	29	56	1
2024-06-21 09:15:00	210	11	68%	30	58	0
2024-06-21 09:30:00	208	10	65%	31	60	0
2024-06-21 09:45:00	206	9	63%	32	62	0

2024-06-21 10:00:00	204	8	60%	33	64	0

For instance, a sample dataset may have entries like Timestamp: "2024-06-21 08:00:00", Voltage: "220V", Current: "15A", Battery Status: "80%", Temperature: "25°C", Humidity: "50%", and Power Failure: "0". Each data entry is recorded at regular intervals, typically every 15 minutes, providing a granular view of the conditions affecting the power supply infrastructure.

Each column in the dataset serves a specific purpose.

- **Timestamp:** Date and time when the data was recorded.
- **Voltage (V):** Voltage measured by the IoT sensors.
- **Current (A):** Current measured by the IoT sensors.
- **Battery status:** The remaining battery capacity of seismic observation stations, as measured by IoT sensors.
- **Temperature (°C):** Ambient temperature recorded by IoT sensors.
- **Humidity (%):** Ambient humidity recorded by IoT sensors.
- **Power failure (Binary, 0/1):** Binary indicator where 1 denotes a power failure event and 0 denotes normal operation.

The data collection frequency is set to capture real-time conditions effectively, facilitating timely responses to any detected anomalies. Anomalies in voltage, current, battery status, and environmental conditions might indicate impending power failures. This comprehensive dataset serves as input for machine learning algorithms designed to predict power failures based on historical patterns and current sensor readings. The systematic approach to data collection and validation, combined with secure data transmission, ensures the integrity and usability of the data, allowing for the development of robust predictive models. This, in turn, supports the efficient management of power supply infrastructure through proactive maintenance and operational strategies.

3.4 Data preprocessing

Data preprocessing is a pivotal phase that optimizes the quality and usability of raw data collected from IoT sensors before it undergoes thorough analysis. The data was meticulously preprocessed to guarantee system consistency and reliability:

Data cleaning

Data cleaning involved rigorous procedures to handle noise, outliers, and missing values. Outliers, which are data points significantly different from others, were identified using statistical methods such as the interquartile range (IQR). The IQR method defines outliers as any data point x that lies outside the range:

$$Q1 - 1.5 \times IQR \leq x \leq Q3 + 1.5 \times IQR \tag{1}$$

Where the first and third quartiles are denoted by Q1 and Q3, and IQR=Q3−Q1.

Once identified, outliers were either corrected based on domain knowledge or removed if deemed erroneous. Missing values were addressed through techniques such as mean imputation, where missing values were replaced with the mean of the available data, calculated as:

$$Imputed\ Value = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

Alternatively, predictive models to estimate missing values based on other variables.

Normalization

Following data cleaning, normalization was employed to standardize the scale of different parameters across the dataset. A common normalization technique used was min-max scaling, which scaled the data to a range between 0 and 1. The min-max scaling formula is:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

This technique guarantees that each feature makes a contribution equally to the examination and avoids attributes with bigger numerical ranges from dominating the analysis simply due to their scale.

Feature extraction

Feature extraction focused on identifying and selecting the most relevant features that significantly influence power supply reliability. Principal Component Analysis (PCA) was utilized as a technique for feature extraction, reducing the dataset's complexity while maintaining its crucial data. By figuring out the main elements that explain the maximum variance in the data, PCA helped in selecting a subset of features that provided the most insightful information about the power supply system's operational status and potential failure points. Mathematically, PCA finds the principal components through resolving the eigenvalue problem for the covariance matrix Σ:

$$\Sigma v = \lambda v \tag{4}$$

Where λ represents the eigenvalues and v represents the eigenvectors. The eigenvectors that match the highest eigenvalues form the principal components.
Each of these preprocessing techniques—data cleaning, normalization through min-max scaling, and feature extraction via Principal Component Analysis—performs a crucial role in enhancing the quality, consistency, and interpretability of the data within the intelligent power supply management system. By preparing the data effectively, these techniques facilitated more accurate analysis and decision-making processes aimed at improving the reliability and efficiency of the power supply infrastructure.

3.5 SeismoGuard ensemble classifier

Power failure prediction is a critical aspect of ensuring the continuous operation and reliability of seismic observation stations, which are essential for monitoring and analyzing seismic activity. The SeismoGuard Ensemble classifier represents an innovative strategy designed specifically to deal with the challenges of predicting power failures in this context. This section details the components and functionality of the SeismoGuard Ensemble classifier, emphasizing its role and effectiveness in enhancing prediction accuracy and robustness.
The SeismoGuard Ensemble classifier integrates multiple machine-learning models into a unified framework tailored for power failure prediction. At its core, the ensemble classifier employs the following base classifiers:

Random forest (RF): RF is selected because of its capacity to manage big volumes of data and robustness against noise. During training, it builds several decision trees and outputs the mean prediction (regression) or the mode of the classes (classification) for each tree. In the context of seismic observation stations, RF effectively captures complex relationships within the data, contributing to accurate predictions of potential power failures. The RF algorithm can be mathematically described as:

$$\hat{y}_{RF} = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{5}$$

where $T_i(x)$ denotes the prediction of the i^th decision tree for the input x, and N is the total number of trees.

Support vector machine (SVM): SVM is suitable for tasks involving higher dimensions data and is particularly efficient in separating classes by discovering the hyperplane that increases the margin between them. This capability makes SVM valuable in classifying seismic data patterns indicative of imminent power failures, thereby enhancing the ensemble's predictive performance. The decision function for SVM can be expressed as:

$$f(x) = sign(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b) \tag{6}$$

where α_i are the Lagrange multipliers, y_i are the class labels, $K(x_i, x)$ is the kernel function, and b is the bias term.

K-Nearest neighbors (KNN): KNN functions according to the idea of proximity-based learning, where new instances are classified based on the majority class of their nearest neighbors. This model is selected for its simplicity and effectiveness in pattern recognition, which is crucial in identifying recurring patterns in seismic data that precede power disruptions. The KNN prediction for a given instance x is:

$$\hat{y}_{KNN} = \frac{1}{k}\sum_{i=1}^{k} y_i \tag{7}$$

where y_i are the class labels of the k nearest neighbors.

1. **Logistic Regression Meta-Classifier:** Serving as the meta-classifier, Logistic Regression (LR) integrates predictions from the base classifiers (RF, SVM, KNN) to produce a final prediction. LR is chosen for its ability to model the probability of a certain class, providing interpretable results and insights into the likelihood of power failures at seismic observation stations. The logistic regression model is defined as:

$$P(y = 1|x) = \sigma(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p) \tag{8}$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$ is the sigmoid function, and β_i are the regression coefficients.
The ensemble classifier follows a stacking approach, where predictions from the base classifiers are aggregated and processed by the meta-classifier to generate a consolidated prediction. This ensemble methodology leverages the complementary strengths of each model, effectively mitigating individual model weaknesses and enhancing overall prediction accuracy. The stacking process can be mathematically represented as:

$$\hat{y}_{Ensemble} = \sigma(\sum_{i=1}^{n} w_i \hat{y}_i) \tag{9}$$

where $\hat{y}_i$ are the predictions from the base classifiers, w_i are the weights assigned to each classifier, and σ is the sigmoid function used by the logistic regression meta-classifier.
The SeismoGuard Ensemble classifier is implemented and validated using real-world data collected from seismic observation stations equipped with IoT sensors. The

dataset includes continuous measurements of critical parameters such as voltage, current, battery health, temperature, and humidity. During implementation, the dataset is divided into training and testing subsets, with the training subset utilized to train the individual base classifiers and the ensemble classifier. Figure 2 demonstrates the flow diagram of the SeismoGuard Ensemble classifier.

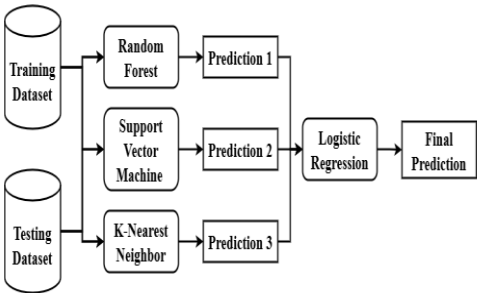

Figure 2: Flow diagram of seismoguard ensemble classifier

By integrating diverse machine learning models within a unified framework, the classifier enhances the operational continuity of these stations during critical seismic events. Its robust performance in predicting power failures ensures timely and efficient management of resources, contributing to improved disaster preparedness and early warning systems. Algorithm 1 shows the SeismoGuard Ensemble classifier.

Algorithm 1: SeismoGuard Ensemble classifier

Input : IoT Sensors Collected Dataset

Output : Power Failure Prediction

Step 1 : **Gathering and Preparing Data**

```
data = collect_sensor_data()
cleaned_data = clean_data(data)
normalized_data = normalize_data(cleaned_data)
features = extract_features(normalized_data)
```

Step 2 : **Data Splitting**

```
train_data, test_data = split_data(features, test_size=0.2)
```

Step 3 : **Training Base Classifiers**

```
rf_model = train_random_forest(train_data)
svm_model = train_svm(train_data)
knn_model = train_knn(train_data)
```

Step 4 : **Stacking and Meta-Classification**

```
train_predictions = {
    'RF': rf_model.predict(train_data),
    'SVM': svm_model.predict(train_data),
    'KNN': knn_model.predict(train_data)
}
meta_model = train_logistic_regression(train_predictions)
```

Step 5 : **Prediction and Evaluation**

```
test_predictions = {
    'RF': rf_model.predict(test_data),
    'SVM': svm_model.predict(test_data),
```

```
    'KNN': knn_model.predict(test_data)
}
final_predictions = meta_model.predict(test_predictions)
metrics = evaluate_performance(final_predictions, test_data)
```

Algorithm 1 starts with data collection and preprocessing, involving cleaning, normalizing, and feature extraction from the raw sensor data. This processed data is then split into training and testing sets. Multiple base classifiers, including Random Forest, SVM, and KNN, are trained on the training data. Their predictions on the training set are used to train a meta-classifier, typically a logistic regression model. Finally, the trained base classifiers generate predictions on the test data, which are then combined and refined by the meta-classifier to produce the final power failure predictions, and the execution of these predictions is evaluated using accuracy, precision, recall, and f1-score metrics.

Overall, the SeismoGuard Ensemble classifier stands as a pivotal tool in enhancing the reliability and efficiency of seismic observation stations through accurate power failure prediction. Its innovative approach underscores its potential to revolutionize how seismic data are monitored and analyzed, ensuring continuous operation and data integrity in the face of seismic events.

1 Experimental results and discussions

The experiments were conducted using the Java programming language and the Weka tool, a widely used machine learning software suite. The focus was on evaluating the performance of the proposed IoT-based intelligent power supply management system against the traditional threshold-based system and SeismoGuard Ensemble classifier against individual classifiers (Random Forest, SVM, KNN, and Logistic Regression) in predicting power failures at seismic observation stations. Data were collected from multiple seismic observation stations equipped with IoT sensors monitoring voltage, current, battery status, temperature, and humidity. The gathered data underwent rigorous preprocessing stages, including cleaning to handle outliers and values that are missing, normalization using min-max scaling, and feature extraction through PCA. To guarantee model robustness and generalization, 10-fold cross-validation was used in the assessment phase. The efficacy of each classifier was evaluated using accuracy, precision, recall, and F1-score.

- **Accuracy:** Accuracy measures the proportion of correct results among all cases.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

- **Precision:** Precision measures the proportion of true positives among predicted positives.

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

- **Recall:** Recall measures the proportion of actual positives correctly identified.

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

F1-score: The F1-score balances precision and recall into a single evaluation metric for classifier performance.

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{13}$$

Where:

❖ TP = True Positives
❖ TN = True Negatives
❖ FP = False Positives
❖ FN = False Negatives

- **Data Transmission Throughput (DTT):** Data Transmission Throughput (DTT) represents the rate at which data is transmitted from IoT sensors to the centralized data processing unit. It is calculated using the formula:

$$DTT = \frac{\text{Total Data Transferred}}{\text{Total Time}} \tag{14}$$

Where:

❖ Total Data Transferred is the quantity of data sent over a given period.

❖ Total Time is the duration of the data transmission period.

- **Packet Delivery Ratio (PDR):** PDR measures successfully delivered data packets as a ratio of the total sent. It is computed using the formula:

$$PDR = \frac{\text{Number of Successfully Delivered Packets}}{\text{Total Number of Packets Sent}} * 100 \quad (15)$$

Where:

Number of successfully delivered packets: Packets received by the centralized unit.
Total number of packets sent: Total number of packets transmitted by the IoT device.
The traditional threshold-based system for power supply management relies on fixed thresholds for parameters such as voltage, current, and battery status, set based on historical data or manufacturer recommendations. It monitors real-time values with sensors and triggers alerts if thresholds are breached, initiating responses like notifying personnel or activating backups. However, it operates reactively, lacking the flexibility to adapt to dynamic environmental changes or unforeseen operational challenges in real time. Moreover, it lacks predictive capabilities, relying on reactive responses rather than preemptive strategies to address potential issues.
The results are summarized in Table 3 and Table 4 below, which compare the performance metrics and efficiency measures of the proposed SeismoGuard Ensemble classifier with individual classifiers and the proposed IoT-based intelligent power supply management system with the traditional threshold-based system.

Table 3: Performance metrics comparison

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest	85	82	87	84
SVM	81	79	83	81
KNN	78	75	80	77
Logistic Regression	79	76	81	78
SeismoGuard Ensemble	90	88	91	89

Table 4: Efficiency measures comparison

System Metric	IoT-based intelligent power supply management system	Traditional Threshold-Based System
Data Transmission Throughput	150 Mbps	100 Mbps
Packet Delivery Ratio (%)	95%	85%

Figure 3 visually depicts the comparison of performance metrics based on a line chart, illustrating the accuracy, precision, recall, and F1-score of each classifier. The bar chart provides a clear and comparative view of how each model performs across these metrics.

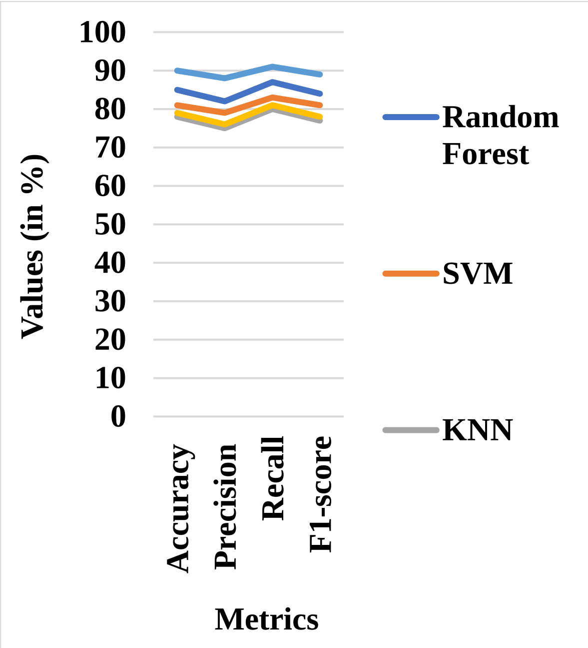

Figure 3: Performance metrics comparison

Figure 3 demonstrates that the proposed SeismoGuard Ensemble classifier outperforms individual classifiers in terms of accuracy, precision, recall, and F1 score. Specifically, the SeismoGuard Ensemble achieves an accuracy of 90%, which is significantly higher compared to Random Forest (85%), SVM (81%), KNN (78%), and Logistic Regression (79%). This improvement comes from the ensemble using multiple classifiers to reduce weaknesses and improve predictions.

Figures 4 and 5 visually present line charts comparing the efficiency measures between the proposed system and the traditional threshold-based system. The bar charts offer a clear and comparative view of key efficiency metrics such as data transmission throughput and packet delivery ratio.

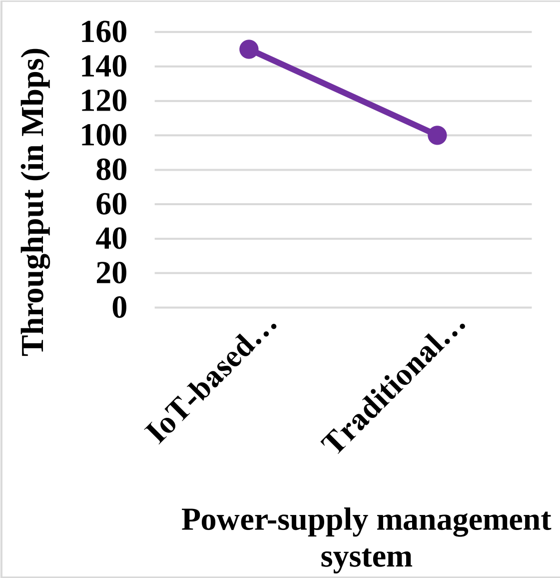

Figure 4: Throughput comparison

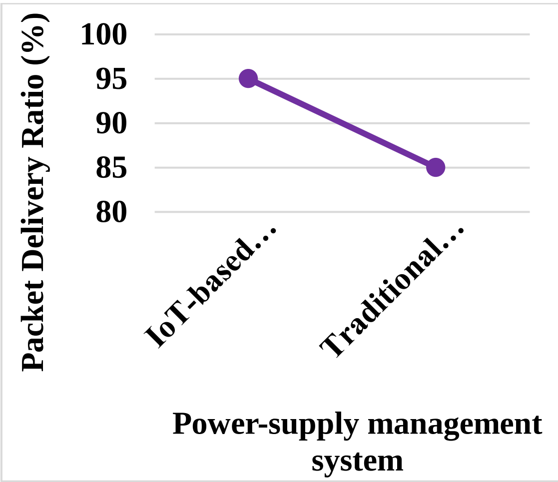

Figure 5: Packet delivery ratio comparison

In terms of efficiency measures (Figures 4 and 5), the proposed IoT-based intelligent power supply management system shows higher data transmission throughput (150 Mbps) compared to the traditional threshold-based system (100 Mbps). This indicates that the integrated approach of IoT-based monitoring and predictive analytics not only enhances predictive accuracy but also ensures reliable data transmission critical for real-time monitoring during seismic events. Additionally, the packet delivery ratio is notably higher at 95% for the proposed system, demonstrating its superior reliability in delivering data compared to the 85% achieved by the traditional approach.

The excellent output of the SeismoGuard Ensemble classifier is due to multiple elements. Firstly, its ensemble learning technique combines Random Forest, SVM, and KNN models with a Logistic Regression meta-classifier, leveraging their complementary strengths to enhance prediction accuracy. Secondly, the system effectively integrates diverse IoT sensor data—including voltage, current, battery status, and environmental conditions—providing a comprehensive view of the power supply system's status and resilience. Continuous real-time monitoring enables prompt anomaly detection, facilitating proactive management of potential power failures. Overall, the experimental results validate the effectiveness of this integrated IoT-based intelligent power supply management system, particularly the SeismoGuard Ensemble classifier, in enhancing reliability and efficiency across seismic observation stations.

4.1 Discussion

The findings in Table 1 show that the SeismoGuard Ensemble classifier surpasses individual classifiers like Random Forest, SVM, KNN, and Logistic Regression on all important metrics. The ensemble's model mixture allows it to capture various trends in seismic data, with 90% accuracy, 88% precision, 91% recall, and an F1-score of 89%. This combined strategy improves prediction accuracy by using each classifier's advantages, presenting a more balanced and dependable result than individual models such as KNN, which struggles because of sensitivity to noise and outliers, or Logistic Regression, which can underperform in nonlinear data situations.

Environmental factors like power outages and transmission delays may have an impact on classifier efficiency. The SeismoGuard Ensemble's resilience stems from its flexibility to these factors, as opposed to simpler models such as KNN or Logistic Regression, which are more sensitive to data fluctuation and noise. However, under extreme circumstances, like serious network congestion or high-latency settings, the ensemble's computational intricacy can cause delays. Conventional models such as Random Forest may execute superior in such situations because of their fewer computational requirements, but they would compromise prediction precision.

Despite its benefits, the SeismoGuard Ensemble has certain drawbacks. Its computational cost can be an issue in real-time applications, where rapid choices are critical. Furthermore, the ensemble may fail with sparse data or overfitting in cases where particular models dominate the voting procedure. Further enhancements could concentrate on enhancing the ensemble's effectiveness and investigating hybrid deep learning models to enhance flexibility, guaranteeing consistent effectiveness across various seismic circumstances.

5 Conclusion and future work

In conclusion, this paper introduces an IoT-based intelligent power supply management system integrated with the SeismoGuard Ensemble classifier, showcasing its significant enhancements in reliability and efficiency for seismic observation stations. Through ensemble learning and real-time IoT sensor data integration, the system accurately forecasts and addresses potential power failures, ensuring uninterrupted operations and data integrity during seismic events. The experimental findings underscore superior performance metrics compared to conventional approaches, underscoring their effectiveness in bolstering disaster preparedness and operational resilience. Moving forward, future studies might examine the use of these methodologies in smart grid systems. By integrating predictive analytics and real-time monitoring into smart grids, similar benefits could be realized, optimizing energy distribution, enhancing grid stability, and promoting sustainable energy practices.

Funding

Langfang Science and Technology Bureau Scientific Research and Development Plan self-financing project (project number: 2023011077)

References

[1] Zhu, W., Hou, A. B., Yang, R., Datta, A., Mousavi, S. M., Ellsworth, W. L., & Beroza, G. C. (2023). QuakeFlow: a scalable machine-learning-based earthquake monitoring workflow with cloud computing. *Geophysical Journal International*, 232(1), 684-693. https://doi.org/10.1093/gji/ggac355

[2] Yang, Z., Dehghanian, P., & Nazemi, M. (2020). Seismic-resilient electric power distribution systems: Harnessing the mobility of power sources. *IEEE Transactions on Industry Applications,* 56(3), 2304-2313. https://doi.org/10.1109/tia.2020.2972854

[3] Omol, E., Mburu, L., & Onyango, D. (2024). Anomaly detection in IoT sensor data using machine learning techniques for predictive maintenance in smart grids. *International Journal of Science, Technology & Management*, 5(1), 201-210. https://doi.org/10.46729/ijstm.v5i1.1028

[4] Truong, G. T., Lee, S. J., Lee, J. E., & Choi, K. K. (2022). Experimental Investigations of the Seismic Performance of a Base-Isolated Uninterruptible Power Supply (UPS) through Shaking Table Tests. *Shock and Vibration*, 2022(1), 2304290. https://doi.org/10.1155/2022/2304290

[5] Abdalzaher, M. S., Elsayed, H. A., Fouda, M. M., & Salim, M. M. (2023). Employing machine learning and IoT for earthquake early warning systems in smart cities. *Energies,* 16(1), 495. https://doi.org/10.3390/en16010495

[6] Hossein Motlagh, N., Mohammadrezaei, M., Hunt, J., & Zakeri, B. (2020). Internet of Things (IoT) and the energy sector. *Energies,* 13(2), 494. https://doi.org/10.3390/en13020494

[7] Sadeeq, M. A., & Zeebaree, S. (2021). Energy management for the Internet of Things via distributed systems. *Journal of Applied Science and Technology Trends,* 2(02), 80-92. https://doi.org/10.38094/jastt20285

[8] Pawar, P., & TarunKumar, M. (2020). An IoT-based Intelligent Smart Energy Management System with accurate forecasting and load strategy for renewable generation. *Measurement*, 152, 107187. https://doi.org/10.1016/j.measurement.2019.107187

[9] Ahmad, T., & Zhang, D. (2021). Using the Internet of Things in smart energy systems and networks. *Sustainable Cities and Society,* 68, 102783. https://doi.org/10.1016/j.scs.2021.102783

[10] Zeadally, S., Shaikh, F. K., Talpur, A., & Sheng, Q. Z. (2020). Design architectures for energy harvesting in the Internet of Things. *Renewable and Sustainable Energy Reviews,* 128, 109901. https://doi.org/10.1016/j.rser.2020.109901

[11] Abdalzaher, M. S., Elsayed, H. A., Fouda, M. M., & Salim, M. M. (2023). Employing machine learning and IoT for earthquake early warning systems in smart cities. *Energies,* 16(1), 495. https://doi.org/10.3390/en16010495

[12] Mia, M. M., Al Hasan, A., Atiqur, R., & Mustafa, R. (2021). The Internet of Things believes in a rule-based smart system to predict earthquakes. *Int J Reconfigurable & Embedded Syst*, 10(2), 149-156. https://doi.org/10.11591/ijres.v10.i2.pp149-156

[13] Falanga, M., De Lauro, E., Petrosino, S., Rincon-Yanez, D., & Senatore, S. (2022). Semantically enhanced IoT-oriented seismic event detection: An application to Colima and Vesuvius volcanoes. *IEEE Internet of Things Journal*, 9(12), 9789-9803. https://doi.org/10.1109/jiot.2022.3148786

[14] Tehseen, R., Farooq, M. S., & Abid, A. (2021). A framework for the prediction of earthquakes using federated learning. *PeerJ Computer Science*, 7, e540. https://doi.org/10.7717/peerj-cs.540

[15] Sharma, K., Anand, D., Sabharwal, M., Tiwari, P. K., Cheikhrouhou, O., & Frikha, T. (2021). A Disaster Management Framework Using Internet of Things-Based Interconnected Devices. *Mathematical Problems in Engineering,* 2021(1), 9916440. https://doi.org/10.1155/2021/9916440