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Towards Sustainable Energy Grids: A Machine Learning-Based Ensemble Methods Approach for Outages Estimation in Extreme Weather Events

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Abstract: The critical challenge of enhancing the resilience and sustainability of energy management systems has arisen due to historical outages. A potentially effective strategy for addressing outages in energy grids involves preparing for future failures resulting from line vulnerability or grid disruptions. As a result, many researchers have undertaken investigations to develop machine learning-based methodologies for outage forecasting for smart grids. This research paper proposed applying ensemble methods to forecast the conditions of smart grid devices during extreme weather events to enhance the resilience of energy grids. In this study, we evaluate the efficacy of five machine learning algorithms, namely support vector machines (SVM), artificial neural networks (ANN), logistic regression (LR), decision tree (DT), and Naive Bayes (NB), by utilizing the bagging ensemble technique. The results demonstrate a remarkable accuracy rate of 99.98%, with a true positive rate of 99.6% and a false positive rate of 0.01%. This research establishes a foundation for implementing sustainable energy integration into electrical networks by accurately predicting the occurrence of damaged components in the energy grid caused by extreme weather events. Moreover, it enables operators to manage the energy generated effectively and facilitates the achievement of energy production efficiency. Our research contributes to energy management systems using ensemble methods to predict grid vulnerabilities. This advancement lays the foundation for developing resilient and dependable energy infrastructure capable of withstanding unfavorable weather conditions and assisting in achieving energy production efficiency goals.

Keywords: extreme events; resilience; energy management resilience; ensemble methods

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1. Introduction

Energy is a vital resource that underpins modern cultural life, making efficient energy management crucial for sustainability. Traditionally, energy grids have relied on fossil fuels for generation, and the conventional grid faces numerous challenges, including capacity limitations and vulnerability to power outages. Extreme weather events, such as hurricanes, pose significant threats to the energy grid and the communities it serves, resulting in substantial damage to critical infrastructure and industries. Resilience, a system's ability to absorb and respond to external events, is an essential quality sought after in vital lifeline systems like energy grids [1]. The rise in power shutdowns triggered by severe weather conditions due to deteriorating climate change has spurred research efforts to enhance community resilience [2]. The high consumption and ever-increasing demand for electricity across commercial, residential, and industrial sectors have prompted researchers to seek new technologies to predict damage to power system components during adverse weather conditions and cyclones [3–7].

Building resilience in energy grids becomes paramount to cope with catastrophic events, like extreme hurricanes. Consequently, this paper focuses on predicting the state of energy grid components in the face of cyclones and windstorms to enhance grid resilience. Accurate prediction of hurricane consequences can significantly improve grid resilience. By anticipating potential impacts and identifying vulnerable parts, the energy system can more effectively prepare for and respond to cyclones and windstorms. This enables better prevention planning and more efficient post-event recovery procedures. Blackouts are becoming increasingly prevalent, with extreme weather events occurring more frequently and severely due to climate change [8]. Several studies have addressed grid resilience and post-disaster restoration in the context of extreme events like hurricanes [9–15]. Three-dimensional SVM was proposed for component classification into damaged, operational, and uncertain categories in response to hurricanes [16]. However, this paper introduces a novel approach based on ensemble machine learning methodologies to predict energy grid component outages during cyclones and windstorms.

In this paper, we employ an ensemble of five machine learning models: logistic regression (LR), support vector machines (SVM), decision trees (DT), artificial neural networks (ANN), and Naive Bayes. The bagging technique is utilized for voting and real-time deployment, classifying energy system components into two classes: damaged and operational, in response to impending hurricanes. While machine learning applications in energy grids have been explored before [17–21], our study distinguishes itself by using ensemble methods to enhance prediction accuracy and address the specific challenges posed by hurricane-induced outages. The primary objective of this paper is to present a power outage prediction model for energy grid components using practical machine learning algorithms. By incorporating ensemble methodologies, we aim to improve prediction accuracy and contribute to the overall resilience of energy grids in the face of extreme weather events. In the subsequent sections, we provide details of our methodology, dataset, experimental setup, and results. Furthermore, we compare the performance of our proposed ensemble model against individual machine learning algorithms, showcasing the superiority of our approach.

This paper contributes to the field of energy grid resilience by introducing an innovative ensemble-based prediction model for hurricane-induced outages. By accurately identifying vulnerable components, our approach enables more effective pre- and post-event planning, ultimately enhancing the resilience of energy grids in the face of extreme weather events.

The rest of the paper is organized as follows: Section 2 presents the problem statement. Section 3 presents the proposed ensemble methods for component outage prediction. Section 4 presents the outcomes of a test system, and Section 6 concludes the paper.

2. Related Work

The energy grid resilience and outage prediction field has seen considerable research in recent years. Various studies have explored different aspects of enhancing grid resilience and dealing with the challenges of extreme weather events, such as hurricanes. This section reviews the relevant literature that has addressed similar topics and methodologies.

2.1. Grid Resilience and Disaster Management

Several works have investigated the resilience of energy grids to extreme events, like hurricanes. Hossain et al. (2021) explored metrics and enhancement strategies for grid resilience and reliability during natural disasters, providing valuable insights into addressing power system vulnerabilities in extreme weather events [2]. Judge et al. (2022) provided an overview of smart grid implementation, highlighting frameworks, impacts, performance, and challenges associated with enhancing grid resilience [3].

Wang et al. (2022) conducted a systematic review of power system resilience from the perspective of generation, network, and load, identifying areas that require special attention to enhance resilience against natural disasters [4]. Umunnakwe et al. (2021) performed a quantitative analysis of power system resilience, highlighting the need for standardization and categorization, and addressing challenges in building resilient power systems [5]. Zhang et al. (2021) proposed stochastic pre-event preparation to enhance the resilience of distribution systems, providing valuable insights into improving the system's ability to withstand extreme weather events [6]. Wang et al. (2022) explored multi-stage stochastic programming to enhance the resilience of integrated electricity and natural gas distribution systems against typhoon natural disaster attacks, highlighting the significance of proactive measures in mitigating damages [7]. Liu et al. (2022) proposed a sequentially preventive model to enhance power system resilience against extreme-weather-triggered failures, offering a systematic approach for minimizing the impact of extreme weather events [8]. A case study on restoring the energy management system along the Gulf Coast of the U.S. after Hurricane Katrina provided insights into post-disaster restoration and telecommunications and power transmission [21]. Deterministic and stochastic models have been proposed for managing resources before and after extreme events, focusing on reducing load curtailment and optimizing restoration schedules [16,19–22]. While machine learning has been applied to energy grid problems, ensemble methods have shown promise in improving prediction accuracy. Three-dimensional SVM was proposed for component classification into damaged, operational, and uncertain categories in response to hurricanes [16]. However, applying ensemble techniques for predicting energy grid component outages during storms still needs to be explored.

2.2. Resilience Index and Multi-Infrastructure Systems

Studies have introduced resilience indices to evaluate the resilience of power systems, considering factors such as distribution efficiency, generation efficiency, and carbon intensity [19]. A methodology for determining the power management systems' resilience index during infrastructure recovery has been proposed, analyzing multi-system networked infrastructures [20]. Research has compared different modeling approaches and strategies for resilience improvement in energy grids [22]. Moreover, predictive models for hurricane-induced outages have been evaluated based on data-driven measurements, component failures, potential customer impact, and outage durations [23].

2.3. Machine Learning Applications in Energy Grids

Machine learning algorithms have been increasingly utilized in energy grid applications. This paper [24] introduces an innovative approach to enhance power grid resilience against wildfires using reinforcement learning (RL). By developing a proactive control system, the study emphasizes the importance of anticipating and mitigating potential damage caused by wildfires. When leveraging RL algorithms, the proposed system optimizes responses to wildfire threats, ensuring efficient actions to minimize disruptions and downtime during fire incidents. The interdisciplinary collaboration between computer science, power systems engineering, and industrial informatics enriches the research's real-world relevance. However, the paper would benefit from providing clearer details on the RL algorithms used, a comprehensive performance evaluation, and a comparative analysis against traditional control strategies or state-of-the-art approaches. Overall, the study offers valuable insights into enhancing power grid resilience in wildfire-prone regions through proactive measures. The authors of [25] presented a machine learning (ML) energy management system to mitigate grid disasters. The study utilizes ML algorithms to optimize the energy management process and enhance grid resilience during disasters. The proposed energy management system can dynamically adapt and respond to changing conditions by integrating ML techniques, ensuring efficient energy distribution and consumption even in disaster scenarios. The interdisciplinary collaboration between ML and energy management specialists enriches the research's practical relevance and applicability. However, the paper could benefit from providing more specific details on the ML algorithms used and conducting a comprehensive performance evaluation to demonstrate the system's effectiveness in disaster mitigation. Overall, the study offers valuable insights into employing ML for energy management in grid disaster scenarios and showcases the potential for enhancing grid resilience through proactive measures. The authors of [26] introduce a novel approach for optimizing post-disaster control in islanded microgrids using multi-agent deep reinforcement learning (MARL). The study focuses on enhancing the resiliency of islanded microgrids after a disaster by leveraging advanced MARL techniques. Through collaborative learning among multiple agents, the proposed approach enables the microgrid to adapt and optimize its control strategies in response to post-disaster conditions, ensuring efficient energy management and rapid recovery. The interdisciplinary collaboration between deep learning experts and microgrid control specialists enriches the research's practical significance and applicability. However, the paper could benefit from providing more specific insights into the MARL algorithm and conducting a comprehensive evaluation to demonstrate its effectiveness in optimizing post-disaster control. Overall, the study offers valuable insights into utilizing MARL for enhancing the resiliency of islanded microgrids and highlights the potential of this approach in improving disaster response and recovery in decentralized energy systems. The authors of [27] present a novel deep reinforcement learning (RL) framework designed to enhance the resilience of distribution systems during extreme weather events. The study focuses on leveraging deep RL algorithms to optimize the response of distribution systems to adverse weather conditions, ensuring reliable and efficient energy distribution even in challenging scenarios. The proposed framework utilizes advanced RL techniques to adaptively learn and improve control strategies, enabling the distribution systems to withstand and recover from extreme weather events effectively. The interdisciplinary collaboration between RL experts and power systems engineers enriches the research's practical significance and applicability. However, the paper could further elaborate on the deep RL algorithms employed and comprehensively evaluate the framework's effectiveness in enhancing distribution system resilience. Overall, the study offers valuable insights into utilizing deep RL for bolstering distribution system resilience and highlights its potential in addressing the challenges posed by extreme weather events in electrical power systems. In this paper [28], the author presents an innovative approach to bolstering power grid resilience by utilizing advanced hybrid machine learning models. The study is motivated by integrating renewable energy resources into intelligent grids, aiming to develop a more sustainable energy system and mitigate climate change's impact. The research emphasizes the vital role of machine learning hybrid models in predicting energy demand and optimizing the utilization of renewable energy sources to improve power grid efficiency and reliability. Specifically, the study focuses on real-time fault detection and remediation techniques, proactively addressing potential issues within the power grid, preventing power outages and minimizing consumer disruption. The results demonstrate the effectiveness of the proposed models, with CNN-GRU achieving the highest accuracy (93.92%) and the lowest MAE and MSE losses at 0.14 and 0.05, respectively. CNN-LSTM and CNN-RNN also performed well, with 93.05% and 92.85% accuracy, respectively. Overall, the research concludes that machine learning hybrid models, including CNN-RNN, CNN-LSTM, and CNN-GRU, can effectively detect and eliminate faults in grid stations, facilitating the integration of renewable energy sources and enhancing power grid efficiency and reliability. The potential of combining machine learning, artificial intelligence, reinforcement learning, and advanced control techniques opens promising avenues for future grid resilience and sustainability. The paper's contributions lie in its practical relevance, addressing critical aspects of modern power grids and providing insights into the potential of advanced machine learning techniques in enhancing power grid resilience while aligning with broader sustainability goals in power systems.

2.4. Exploring Diverse Original Classification Methods for Predicting Energy Grid Vulnerabilities

The Human Knowledge Database utilized in this study encompasses a diverse range of classification methodologies rooted in the expertise of human operators [29]. These methods reflect the historical practices employed to predict energy grid vulnerabilities during extreme weather conditions [30]. One such approach involves the formulation of heuristic rules, wherein experts have devised rule sets informed by their domain knowledge [31].

For instance, rules linking heightened wind speeds and heavy rainfall to an elevated risk of power outages exemplify this strategy. Moreover, pattern recognition techniques have been leveraged, enabling experienced human operators to discern recurring combinations of weather factors that have historically precipitated grid vulnerabilities [32].

The authors of [33] constructed index-based methods, exemplified by creating a "Physical Vulnerability Index" that amalgamates various weather parameters, such as rainfall intensity, wind speed, and temperature. Furthermore, human operators have harnessed decision trees to sequentially navigate weather conditions based on well-established trees developed over years of experiential insights. Domain-specific heuristics have evolved through time, fostering a nuanced comprehension of how distinct weather conditions impact diverse energy grid components, thereby enriching the classification process. Experience-based categories that help an operator to predict weather conditions ranging from "low risk" to "moderate risk" and "high risk" have emerged from intuition and accumulated experiences with past weather events [34].

Moreover, time series analysis has been instrumental, enabling human experts to scrutinize temporal weather and vulnerability trends, uncovering valuable correlations [35]. These methodologies, rooted in human expertise, form a foundational basis for the study's investigation into energy grid vulnerability prediction, further enriched by integrating contemporary computational machine learning techniques.

Our work distinguishes itself by proposing an ensemble method based on machine learning to predict energy grid component states during hurricanes. By leveraging multiple machine learning algorithms and the bagging technique, our approach aims to provide accurate and reliable predictions, enhancing grid resilience and disaster preparedness. In the subsequent sections, we present our proposed ensemble-based prediction model's methodology, dataset, experimental setup, and results. A comparative analysis in the discussion section with individual machine-learning algorithms further demonstrates the effectiveness of our approach in predicting hurricane-induced outages.

3. Problem Statement

The efficiency and quality of each component in the grid both during and after extreme weather events are considered when determining the resilience index. There has been a growing need to predict the status of the grid's components and maintain its resiliency in every condition and case. During extreme weather, a grid components status can be classified as operational (in service) or damaged (out of service). Several features have been taken from historical data using a case study of the NEOM region in the north of Saudi Arabia, which could be used to categorize the state of each component into two statuses (operational or damaged). In this paper, ensemble methods are used to predict the components' state and to distinguish between operational and damaged status. The features that are used to determine this are discussed in the section that follows, along with a brief introduction to ensemble methods. These three papers [36–38] have provided state-of-the-art reviews on power grid resilience and several machine learning-based techniques; they serve as motivation for us to address the problems reported in their studies.

4. Proposed Ensemble Method for Outage Prediction

In machine learning (ML), ensemble learning combines the results of various classifications made using ML in order to improve accuracy and increase attack classification detection performance. An overview of the machine learning and ensemble methods is given in this section. Various algorithms are used for the dataset, and the accuracy score is computed until the highest score is achieved. While the testing is completed online in real-time deployment mode, the training is performed offline using historical data. Combining homogeneous and possibly heterogeneous algorithmic classifiers in ensemble learning (EL) might result in a more accurate predictive model with a faster inference time [39].

4.1. Insights into Training Data Scenarios

To provide a comprehensive understanding of the original classification methods employed by human experts, we have developed a flow diagram that illuminates insights into the training data scenarios used in energy grid forecasting during extreme weather events. This diagram, depicted in Figure 1, captures the key factors and decision points that guided human operators in their classification process.

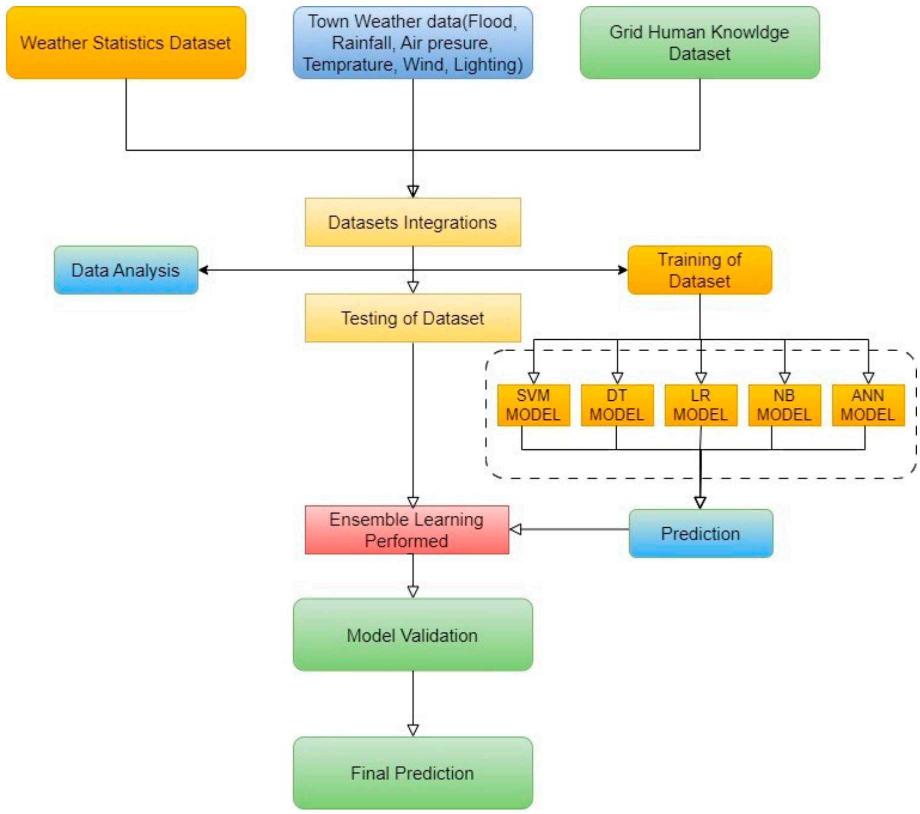

Figure 1. Flow Diagram of Insights into Training Data Scenarios.

The flow diagram begins with weather data, weather statistics dataset, and grid station human knowledge database, then identifies historical weather data and real-time weather forecasts as foundational inputs for the classification process. Human operators then consider a range of environmental parameters, such as wind speed, temperature, humidity, and precipitation levels, as well as grid-specific factors, including load demand, transmission line vulnerabilities, and equipment conditions.

Crucially, the diagram highlights the iterative nature of the classification process, wherein human experts continually validate and update the classification based on ongoing observations and feedback. This iterative loop reinforces the adaptability of human operators and underscores the significance of domain expertise in responding to dynamic conditions. By visualizing the insights into training data scenarios, the flow diagram clearly depicts the multifaceted considerations that shape human classification methods. This visualization enriches the context of our research and underscores the importance of integrating such domain knowledge into our machine learning-based approach. In the next section, we will discuss how our machine-learning ensemble leverages these insights to complement and enhance its predictive capabilities, ultimately contributing to the resilience of energy grids during extreme weather conditions.

4.2. Support Vector Machines (SVM)

SVM is a classification method that forms a separation hyperplane among two categories. The support vector machine (SVM) model utilized in this study combines the strength of traditional statistical methods with analytical simplicity, making it particularly effective, even for small datasets. For this experiment, linear SVM classifiers were selected due to their faster training time and lower computational complexity compared to non-linear SVMs. Additionally, linear SVM classifiers are well-suited for high-dimensional data applications, eliminating the need for additional feature engineering [40].

The SVM algorithm can be described using the following variables:

$$Training\ data\ D = \{xi,\ yi\}Ni = 1 \tag{1}$$

$$Input\ vectors\ xi = (x(1)i,\ \ldots,\ x(n)i)T\ \in\ \mathbb{R}\hat{}n \tag{2}$$

$$Target\ labels\ yi\ \in\ \{-1, +1\} \tag{3}$$

The conditions for SVM are defined as:

$$yi[wT\Phi(xi) + b]\ \geq\ 1,\ for\ i = 1,\ \ldots,\ N \tag{4}$$

Here, w represents the weight vector, and b is the bias term. The non-linear transformation function is denoted as:

$$\Phi(\cdot) :\ \mathbb{R}\hat{}n\ \rightarrow\ \mathbb{R}\hat{}nK \tag{5}$$

The SVM algorithm finds a separating hyperplane between two parallel hyperplanes given by:

$$wT\Phi(xi) + b = 0 \tag{6}$$

with a margin width of $2\|w\|2$.

The classifier's decision is made using the formula:

$$sgn(wT\ \Phi(xi) + b) \tag{7}$$

The final SVM function is formulated as:

$$sgn\left(\sum Ni\ \xi i\ yi\ K(xi,\ xi) + b\right) \tag{8}$$

In this way, the SVM model effectively classifies data points into distinct classes, contributing to accurate predictions and robust performance in the experiment.

4.3. Logistic Regression (LOR)

Logistic Regression is a method to predict values for the dependent variable between 0 and 1 using the regression formula [41]:

$$y = \hat{e}(b0 + b1x1 + \ldots + bnxn)\ /\ (1 + e\hat{}(b0 + b1x1 + \ldots + bnxn)) \tag{9}$$

Additionally, we can transform the probability "p" of the dependent variable "y" as follows:

$$p\prime = log\_e(p\ /\ (1 - p)) \tag{10}$$

where $p\prime$ can range between $+\infty$ and $-\infty$. The transformed values will be used in the ordinary linear regression, and the final equation becomes:

$$p\prime = b0 + b1x1 + b2x2 + \ldots + bnxn \tag{11}$$

4.4. Decision Trees (DT)

Decision trees [42] are one of the important methods in machine learning that work on linear as well as non-linear data. These algorithms work according to the rules made on data. The accuracy of the decision trees heavily depends on the decision to split the tree, i.e., deciding on the correct number of splits. The basic motive of a decision tree is to predict the target variable's value based on the simple decision rules extracted from the related features set. A decision tree employs a tree-like model to represent options and their potential results, including several variables and chance event outcomes. In a decision tree, the internal node is the depiction of the applied test, and the tree branch represents the output of the test performed. A decision tree comprises a tree flowchart-like structure that can handle both categorical as well as numerical data. This strategy is different for regression as well as classification trees. Therefore, multiple algorithms are utilized to divide a node into at least two sub-nodes. The nodes are partitioned by the decision trees on all the variables which are available and the division that yields identical sub-nodes is selected. Initially, the algorithm starts from the decision's tree root node to predict the class in a given dataset. Then, the values of the root are compared with the record attribute present in the real dataset. Depending on this comparison, a jump is made to a different branch to start with the next node.

The value of the attribute is re-compared with the value of other sub-nodes for the next node to move in a further direction. This procedure continues until the algorithm reaches the destination node of the tree, i.e., leaf node. The entire process can be summarized by the following steps.

1. Start with the root node of the tree 'R'. This node includes the entire dataset.
2. Determine the best attribute of the options in the dataset with the help of some attribute selection measure (ASM).
3. Splitting the root node 'R' into subsets 'S', which contain all the possible values for the best attributes.
4. The node, i.e., decision tree node which has the best attribute, is generated.
5. By utilizing the subsets of the entire dataset as constructed in step no. 3, generate new decision trees recursively.
6. Continue with this procedure until further splitting of the node is not possible and the current node will be the final node, i.e., the leaf node.

To select the attribute in step 2, there are several methods, but the most widely used ones include information gain and the Gini index. The number of subsets that the nodes should reach is determined by these measurements.

4.5. Artificial Neural Network (ANN)

ANN is an essential part of the machine learning method that is now the most widely used in research and development. ANN's draw inspiration from the biological human brain, which is a network with potentially 60 trillion linked neurons that execute network patterns of decision-making [40]. This fundamental concept serves as the foundation for the artificial neural network process, which begins with very basic, easily comprehendible interconnected neurons operating as a single processor. Consequently, from the primary concept of the information processing cycle, ANNs perform complex mathematical formulations to arrive at optimal results for any given dataset or problem segment. In developing the models in this study, different variants of artificial neural networks (ANNs) were deliberately selected to explore and harness their unique capabilities for the specific task at hand. ANNs are known for their ability to model complex relationships and patterns in data, making them suitable for various applications. Multiple ANN variants allowed the researchers to evaluate their performance under different scenarios and data characteristics. For instance, a feedforward neural network was chosen for its simplicity and effectiveness in handling structured data. By leveraging these diverse ANN architectures, the study aimed to comprehensively assess their strengths and limitations in addressing the specific challenges of the problem domain, ultimately paving the way for more informed decisions and model selection in real-world applications. There are also different types of activation functions that can be used in ANN, but the simplest one is the rectified linear activation function, or *ReLU*. The *ReLU* function normally chooses the highest value for the output from the linear combination of inputs from the previous nodes [43]. *ReLU* was chosen since it produces either all zeros or all ones as its output. In addition, the grid includes all numerical functions within a specific range and is either stable (represented by "1") or unstable (represented by "0") with regard to our dataset. The "sigmoid" function is used as an activation function for the output layer because the dataset only has two prediction classes, indicating that the dataset will be classified logistically.

$$ReLu = 0 \; if \; x < 0 \tag{12}$$

or

$$ReLu = 1 \; if \; x \geq 0 \tag{13}$$

where the $ReLU$ function is defined as follows: $f(x) = max(0, x)$ meaning that the output of the function is maximum between the input value and zero, and the input value is x. This can also be written as:

$$ReLu = 1 \; if \; x \geq 0 \tag{14}$$

The adaptive optimization method, often known as "Adam", is an optimization approach which is most widely used to forecast grid stability to enhance the performance of ANN [44]. The Adam optimizer function can aid in ANN network weight optimization. It also aids in improving the ANN model's learning rate.

4.6. Naive Bayes

The Naive Bayes model is a machine learning classification model known for its independence assumption, meaning that other attributes do not influence the probabilities of one instance. It has been observed that the Naïve Bayes classifier often produces accurate results. However, it can underperform due to issues arising from training data noise, variance, and bias [44]. According to the algorithm explanations in [44], the features or vectors are presented as X = ($X1$, . . ., Xn) from domain Di, where lowercase "x" represents the value of a vector. The unobserved class C is one of the "m" values represented as C ∈ {0, . . ., m^{-1}}, and it is obtained by g(x), where g: Ω → {0, . . ., m^{-1}}, and Ω = $D1$ × . . . × Dn.

The Naïve Bayes discrimination function is given as:

$$f\_NB(x) = \prod(j = 1 \; to \; n) \; P(Xj = xj \mid C = i) \; P(C = i) \tag{15}$$

4.7. Bagging

There are three main classes or methods of ensemble learning (EL), including bagging, stacking, and boosting. In our study, we used the bagging technique. The process of bagging involves averaging the results of numerous decision trees which have been fitted to distinct samples of the same dataset. Consider a training set $T = t_1, \ldots, \; t_n$ and responses $L = l_1, \ldots, \; l_n$. The bagging algorithm selects a random sample and replaces the training set periodically (P times) before fitting trees of various sizes to these samples. The process depicted in Algorithm 1 can be used to accomplish this.

$$\hat{f} = \frac{1}{P} \sum_{b=1}^{P} f_b \; (X') \tag{16}$$

Algorithm 1 Bagging classifier

1: **for** $b = 1, \ldots P$: **do**
2: Sample, with replacement, n training examples from T, L; call these Tb, Lb.
3: Train a classification tree, fb on Tb, Lb.
4: Predictions for samples that were unseen x0 after training.
5: Calculate the final predictions from each individual fb on x0 to take the average of all predictions for regression or the majority vote for a classification task by using Equation (5).
6: **end for**

4.8. Features of Component

An individual quantifiable feature of an observed phenomena is what machine learning refers to as a "feature" [41]. The effectiveness of the classification approach highly depends on the choice of discriminating, independent, and informative variables. To figure out the status of the components just after a hurricane strike, major features might be defined. In [25], the wind speed and the distance between each component from the hurricane's center have been suggested in response to a hurricane. These features provide sufficient information, but they do not reveal information about the component itself. In this paper, wind speed, wind direction, solar irradiance, pressure, temperature, and rain are examined as six key features to predict the state of each component as a result of the hurricane.

4.9. Evaluation Metrics

There are numerous evaluation criteria that can be used to assess the classification method's acceptability and reliability as found in the literature. The most standard method for assessing a classification system is accuracy, which is usually calculated as the ratio of the number of accurate predictions to the total samples in the testing set.

$$Accuracy = \frac{correct\ classification}{all\ classification} \tag{17}$$

Precision (P) is the ratio of actual predicted outages to overall predicted outages and is defined as:

$$Precision\ (P) = \frac{True\ Positive}{Total\ Predicted\ Positive} \tag{18}$$

Recall (R) is the ratio of accurately predicted outages to all actual outages and can be calculated as follow:

$$Recall\ (R) = \frac{True\ Positive}{Total\ Actual\ Positive} \tag{19}$$

$F1$-Score evaluation of historical data is used to test the efficacy of the produced decision boundary.

$$F1 = \frac{2PR}{P+R} \tag{20}$$

4.10. Ensemble Classifier

Ensemble classifiers in this study differ from existing ensemble approaches that combine ML classifiers to improve accuracy. The following are some of the most common models utilized:

4.10.1. Mean Ensemble Voting

This ensemble type aims to find the average decisions of all base classifiers as depicted by the equation adapted from [32]:

$$\hat{y} = \text{Average}\ \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_k\} \tag{21}$$

4.10.2. Weighted Ensemble Voting

To predict the class label $\hat{y}$, considering the weight ω related to classifier f, the formula used is:

$$\hat{y} = \sum (\omega_i \times \hat{y}_i) / \sum \omega \tag{22}$$

where ω is the characteristic function and A is the set of class labels, computed using the formula:

$$\omega_i = f_i \in A \tag{23}$$

4.10.3. Accuracy in Weighted Ensemble Voting

This approach operates similarly to weighted accuracy, where the weight ω is replaced by the accuracy of each base classifier. The accuracy is calculated by:

$$\text{Accuracy} = \left(\sum \text{True Positive} + \sum \text{True Negative}\right) / \sum \text{Total Population} \tag{24}$$

4.10.4. Proposed Ensemble Voting

The ensemble approach adopted and modified in this study is "Accuracy as Weighted Ensemble Voting". The weight represents the accuracy of each classifier, which is already used in classification. The proposed approach uses confusion matrices and a numerical array to store accurate prediction values. The significance of the proposed ensemble lies in utilizing the accuracy of each class or label among all base ML classifiers. Rather than using overall accuracy as an absolute measure, this approach considers the strength of each base classifier, making it a more suitable approach for the labeling process. Algorithm 1 illustrates the calculation of weights for base ML classifiers and the process of combining them for ensemble voting. Algorithm 2 describes the ensemble voting algorithm.

Algorithm 2 Ensemble Voting Algorithm

Require: X: A data stream of sentences inserted from a file.
Require: Y: A label of the sentences
Require: C lf (i): Number of algorithms used [ANN, SVM, Naive Bayes, Decision Tree, Bagging Classifier].
Ensure: W: An array of weights assigned for each C lf (i)
Ensure: Voting_Accuracy: Represents the proposed ensemble voting model.
{Data preprocessing stage}
  Tokenize sentences in X
  Remove spaces and stop words in X
  Convert X to numerical representation using a converter function
  Convert labels (Y) to numerical representation using a converter function
  Split data into training and testing portions:
$$train\_data(X,\ Y),\ test\ \_data(X,\ Y)$$
  for each model in C lf (i) **do**
    C lf (i) $\leftarrow$ f it $(train\_data\ (X,\ Y)$
    $P\ (y\prime)$ $\leftarrow$ Predict $(test\_data\ (X))$
    $Result$ $\leftarrow$ Compare $(P\ (y\prime),\ Y)$
    Conf (i) $\leftarrow$ Calculate_Confusion_matrix $(Result)$
    $Accuracy(i) \leftarrow \frac{Result}{Y \times 100}$
  end for
{Give a weight for each model}
  Combine the diagonals of all confusion matrices into one matrix:
$$\text{Conf\_matrix} \leftarrow [[\text{Conf}\ (i\ :).\ \text{diagonal}]]$$
Find the maximum of each column that will represent the algorithm weight:
$$W \leftarrow \text{max\_column}\ (\text{Conf\_matrix}(i))$$
V_result $\leftarrow$ Voting_algorithm (C lf (i), $W\ (i)$)
Voting_Accuracy $\leftarrow \frac{V\_result}{Y \times 100} = 0$

5. Discussion

We proposed an ensemble model in which several models (commonly referred to as weak learners) were trained to address the same issue and were then combined to provide superior outcomes. The basic hypothesis is that, by properly combining some of these weak models, we can create more accurate and/or resilient models that can be used as building blocks for creating sophisticated models. The aim of ensemble methods is to improve performance by combining some of these weak learners to generate stronger learners (or ensemble models) that have less bias and/or variation. We have used the ensemble of five machine learning models, which are logistic regression (LOR), support vector machines

(SVM), decision trees (DT), artificial neural network (ANN) and Naive Bayes. We have applied bagging technique to vote for and predict the final output. Bagging is a homogeneous model of weak learners that learn independently in parallel and combine their output to determine the average of these independent models' predictions (for regression) or the majority vote (for classification). The final output was obtained using different classifiers to predict the components' state. Then, the performance of all the methods is evaluated using various performance evaluation techniques to find the best method. This ensemble model is trained to classify components into two categories (damaged and operational) in response to an impending hurricane. For each element, the model is trained on a variety of features (wind speed, wind direction, solar irradiance, pressure, temperature, and rain).

In this work, different data preprocessing techniques were used, including data transformation, data cleaning, missing data handling, and resampling. The purpose of preprocessing is to transform the raw data into a processed form to attain more accuracy and increase the performance of the model. The trained ensemble model determines the state of each component in accordance with the predicted hurricane. In order to lessen the associated aftermath, it can be extremely important to schedule available resources in a proactive manner in reaction to these events. Security-constrained unit commitment (SCUC), a crucial decision-making mechanism in the operation of the energy market, has been the subject of in-depth study [45]. The event-driven security-constrained unit commitment (E-SCUC) problem is resolved to produce an ideal and resilient schedule of the resources in response to the hurricane once the state of each system component is estimated [38].

5.1. Experiment Details

In this section, we provide a comprehensive overview of the experimental setup and details that, in the proposed ensemble approach for power grid component state prediction, we were told to use to assess the initial sample size's impact on our model's accuracy. The dataset was preprocessed according to the methodology outlined in the proposed model section. Data transformation, cleaning, handling missing data, and resampling techniques were applied to ensure the data's quality and suitability for training and testing the ensemble model. To investigate the effect of the initial sample size, we performed data splitting, dividing the dataset into training and testing sets. The split was conducted with 70% of the data allocated to the training set and 30% to the testing set. This split proportion was chosen based on the ratio of the number of classes used and the overall dataset size. By using the 70–30 split, we ensured that each class was well-represented in training and testing data, maintaining a balanced dataset throughout the experiment. We conducted a series of experiments with various data split percentages to explore the impact of different initial sample sizes on prediction accuracy. The initial sample sizes were adjusted from 60–40 to 80–20 in 5% intervals. For each split percentage, we evaluated the performance of our model on the power grid component state prediction task. The prediction accuracy was used as the primary evaluation metric to assess the performance of the ensemble method. We measured the accuracy of the models in correctly predicting the state (damaged or operational) of each power grid component in response to an impending hurricane. The experimental results revealed essential insights into the relationship between the initial sample size and the accuracy of the ensemble model. We observed that, as the sample size increased, the prediction accuracy of the models improved. Larger initial sample sizes allowed the ANN models to learn more effectively from the data, leading to enhanced generalization and better performance. Based on the experimental findings, we concluded that the initial sample size significantly impacts the accuracy of the ANN models in the proposed ensemble approach for power grid component state prediction. A more significant sample size results in improved prediction accuracy, providing better resilience and preparedness in the face of extreme weather events. The 70–30 data split used in the ensemble model was found to balance training and testing data, ensuring robust and accurate predictions. These experimental results validate the effectiveness and reliability of our proposed approach for enhancing power grid resilience.

5.2. Results

Table 1 compares evaluation metrics of the five models: logistic regression (LR), decision tree (DT), support vector machine (SVM), Naive Bayes (NB), and artificial neural network models (ANN). As can be noticed, among the trained models, bagging and the logistic regression achieved the best overall classification accuracy, with values of 0.99979 and 0.99974, respectively; they also gave the highest performance in precision, recall, and *F*1 score.

Table 1. Comparison of the performance of five models using the bagging classifier.

	Evaluation Metrics			
Models	**Accuracy**	**Precision**	**Recall**	***F*1-Score**
LR	99.96	99.95	99.97	99.96
DT	99.95	99.95	99.96	99.95
SVM	99.92	99.89	99.94	99.91
NB	98.91	98.96	98.57	98.76
ANN	60.69	33.44	50.00	40.08
Proposed Ensemble Classifier	99.90	99.96	99.98	99.96

Table 1 presents the performance metrics of various machine learning algorithms evaluated in this study for forecasting smart grid device conditions during extreme weather events. Notably, the presented results demonstrate the remarkable accuracy rates achieved by support vector machines (SVM), logistic regression (LR), decision tree (DT), and Naive Bayes (NB), where accuracy levels consistently exceeded 98%. These findings underscore these models' proficiency in handling the problem domain's intricacies. However, an intriguing observation emerges when considering the artificial neural network (ANN) performance. The ANN displays comparatively lower accuracy in isolation, achieving approximately 60.69%. This lower performance indicates the inherent complexities and challenges of modeling such dynamic and multifaceted systems. While the isolated performance of the ANN may seem counterintuitive, it aligns with our deliberate strategy to use ANN as a baseline for comparison and as a catalyst for future research directions. The suboptimal performance of the ANN serves as a pivotal point for motivation, guiding our exploration of more advanced techniques, such as convolutional neural networks (CNN), gated recurrent units (GRU), and long short-term memory (LSTM) networks, which hold the potential to uncover deeper insights and elevate our ensemble-based forecasting methodology.

Figure 2 below shows the performance of the five models, i.e., the logistic regression (LR), decision tree (DT), support vector machine (SVM), Naive Bayes (NB), and artificial neural network model (ANN).

Figure 3 below shows the confusion matrices of the five models of machine learning algorithms.

When comparing the five algorithms in Table 2, the artificial neural network shows higher error than the other algorithms, followed by Naïve Bayes, support vector machine, decision tree, and finally logistic regression.

Table 2. Performance Comparison of Machine Learning algorithms.

ML Models	Mean Absolute Error	Root Mean Square Error
LR	0.00025	0.016100
DT	0.00057	0.023800
SVM	0.00088	0.029688
NB	0.01223	0.110617
ANN	0.326178	0.571120

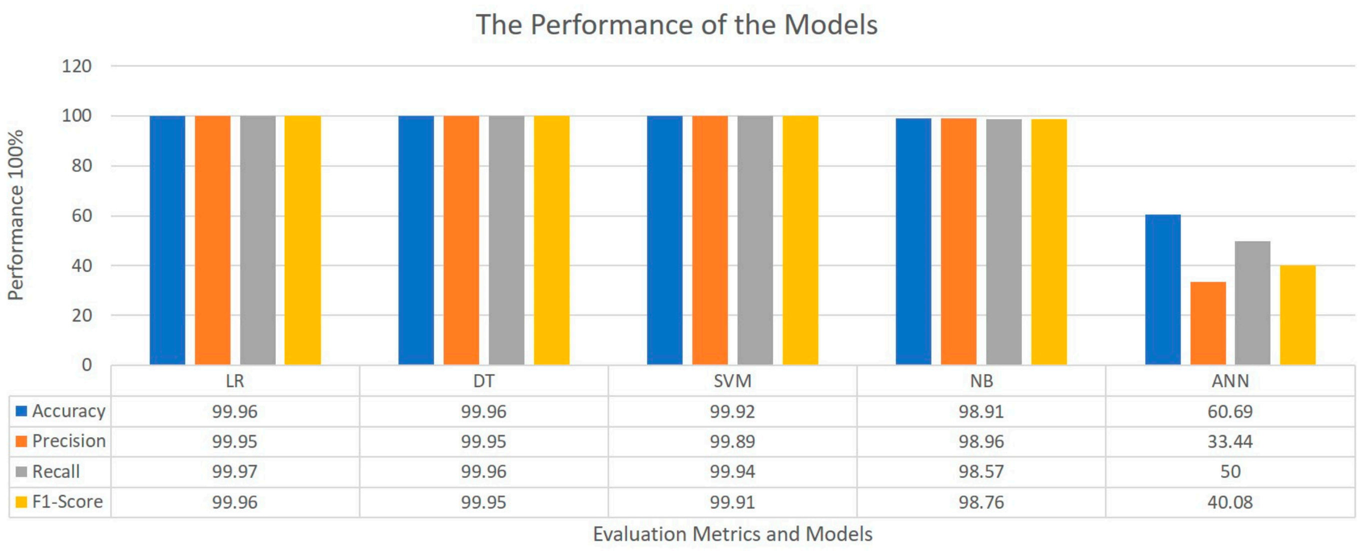

Figure 2. Performance of the Models.

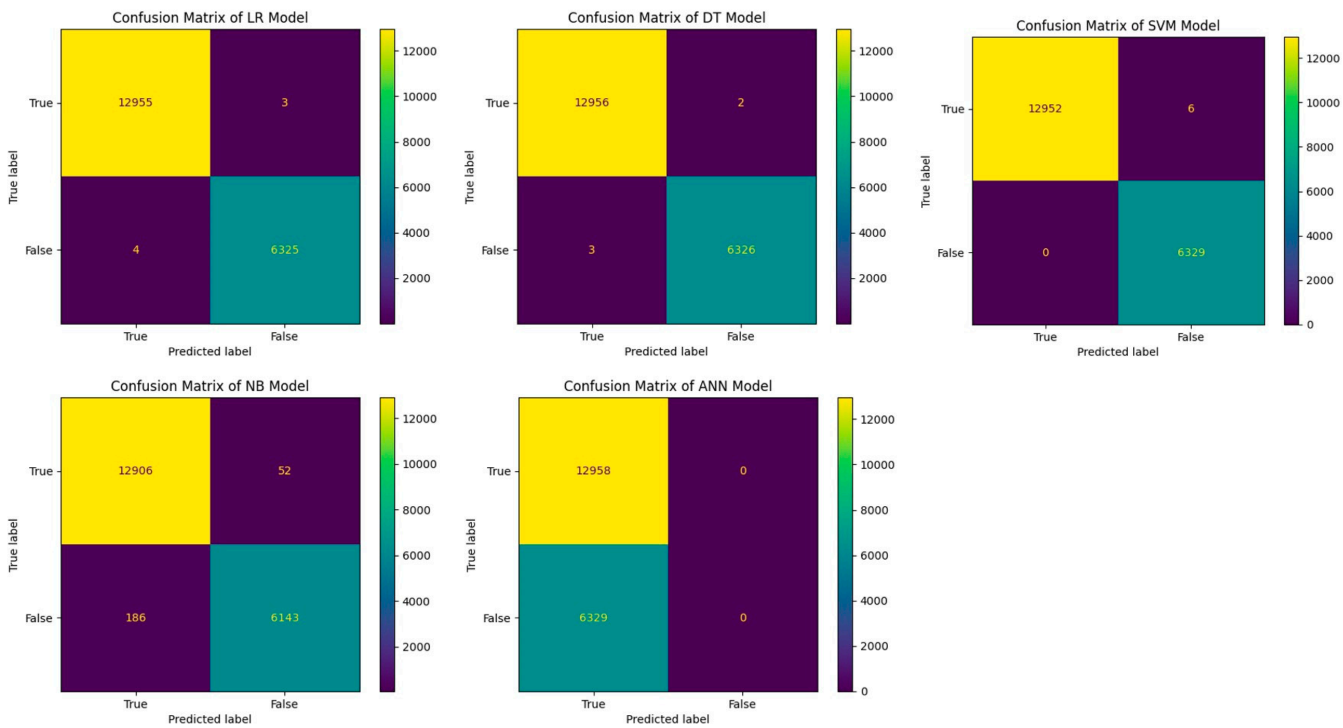

Figure 3. Confusion matrices of the models.

Figure 4 shows the accuracy of artificial neural network model (ANN), which is 0.9995, while the loss is shown in Figure 5.

Table 3 presents the classification of the components in this case study. Based on the previously mentioned characteristics, the components are classified into two categories: operational and damaged. Seven components are classified in the damaged class, specifically, numbers 13, 14, 19,292, 59, 30,280, 66,164, and 999, and ten components were categorized in the operational class, specifically, numbers 3, 5, 9, 53, 67, 47, 17, 14,161, 30,282, and 979.

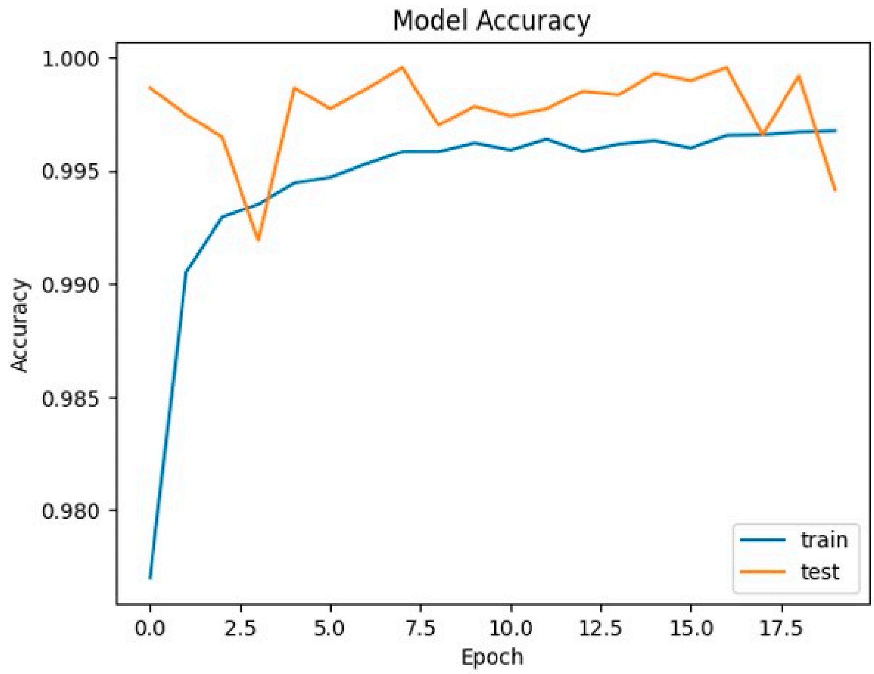

Figure 4. Accuracy Curve.

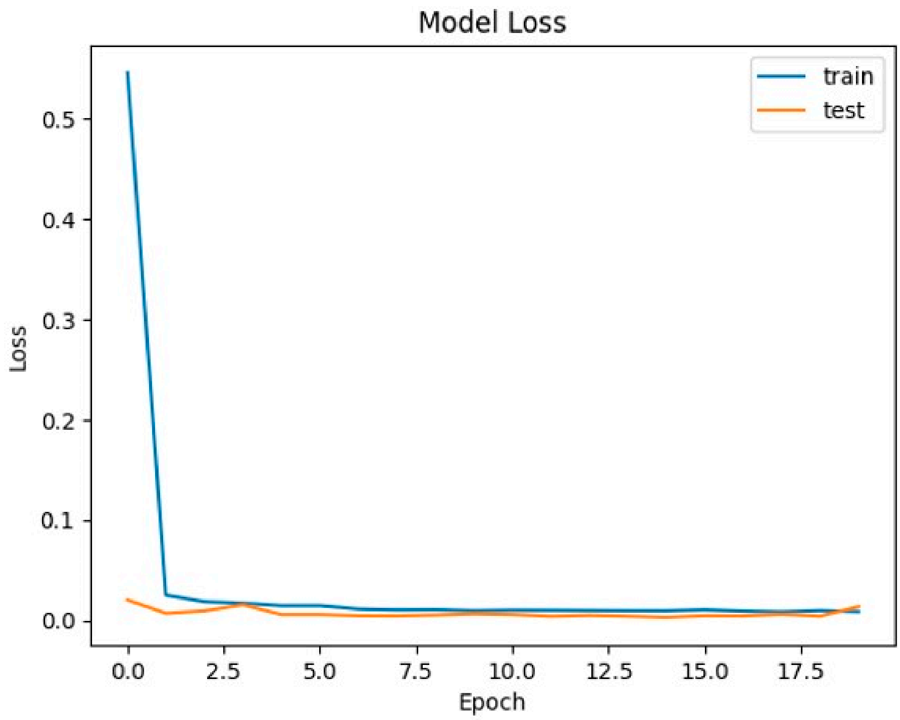

Figure 5. Loss Curve.

Table 3. Classification of components.

Com No. [1]	Pre(hPa) [2]	Tem(C) [3]	WSp (m/s) [4]	WDir (deg) [5]	SR(W/m^2) [6]	R (mm) [7]	Class
3	1012.917	14.429	2.667	106.699	0	0	Operational
5	1013.247	14.390	3.141	102.371	0	0	Operational
9	1012.876	20.277	2.120	156.114	333.671	0	Operational
13	1012.829	20.601	2.794	214.971	548.236	0	**Damaged**
14	1012.648	20.785	2.765	209.89	412.398	0	**Damaged**
53	1015.040	12.054	3.515	65.738	0	0	Operational
59	1016.296	20.209	4.081	302.274	675.432	0	**Damaged**
67	1016.969	15.482	1.834	121.943	0	0	Operational
47	1015.900	13.810	2.805	73.3100	0	0	Operational
17	1012.672	19.765	0.800	186.866	0	0	Operational
14,161	1002.664	28.213	3.968	132.535	0	0	Operational
19,292	1009.626	23.466	2.178	149.937	0	0	**Damaged**
30,280	1006.045	28.311	5.043	274.751	89.396	0	**Damaged**
30,282	1005.931	27.403	0.709	308.247	89.396	0	Operational
66,164	1001.678	28.620	2.125	154.453	0	0	**Damaged**
979	1016.091	16.468	1.264	72.3990	0	0	Operational
999	1015.462	19.598	5.260	251.148	518.165	0	**Damaged**

[1] Component number. [2] Pressure (Hectopascal Pressure Unit), [3] Temperature (Celsius Unit), [4] Wind Speed (meter/second Unit), [5] Wind Direction (Degree Unit), [6] Solar Irradiance (Watts per square meter Unit), [7] Rain (millimeter Unit).

6. Conclusions

In this paper, we proposed an ensemble method that leverages the strength of five machine learning models, namely support vector machines, logistic regression, decision trees, artificial neural networks, and Naive Bayes, to classify power grid components into either damaged or operational states in response to imminent hurricane conditions. The experiments validated our proposed method's efficiency in accurately categorizing components based on six crucial features. This ensemble approach led to a more resilient power grid, with the bagging ensemble classification method showcasing the best overall classification accuracy of 99.9%. Our model also achieved outstanding performance in precision (99.96), recall (99.98), and *F*1 score (99.96). Our approach outperformed their best-performing SVM model with the Gaussian kernel. These results demonstrate that our ensemble method excels in accurately predicting the state of power grid components during extreme weather events, significantly improving power grid resilience. The success of our ensemble method showcases its potential to play a critical role in future power grid planning and preparedness, ensuring a more resilient and reliable energy system in the face of adverse weather condition.

7. Limitations

While our research presents a promising approach to forecasting smart grid device conditions during extreme weather events using ensemble methods, certain limitations warrant discussion. Notably, the isolated performance of the artificial neural network (ANN) yielded accuracy levels lower than anticipated, achieving approximately 60.69%. This outcome highlights the intricate challenges inherent in modeling the complex dynamics of energy grids during extreme conditions. The limitations of the ANN underscore the importance of exploring alternative techniques to capture the intricate relationships within the data. Our study acknowledges these limitations and paves the way for valuable future research avenues. The suboptimal performance of the ANN catalyzes our commitment to delve into more sophisticated models, such as convolutional neural networks (CNN), gated recurrent units (GRU), and long short-term memory (LSTM) networks. These advanced architectures are anticipated to better capture the temporal and spatial patterns inherent in energy grid behavior, potentially leading to enhanced predictive accuracy.

8. Future Work

In future research, we aim to further enhance the performance of our ensemble classification model by incorporating more advanced machine-learning techniques. Specifically, we plan to explore the integration of long short-term memory (LSTM), gated recurrent unit (GRU), convolutional neural networks (CNN), and bidirectional recurrent neural networks (BRNN) as part of our ensemble approach. These state-of-the-art models have demonstrated promising capabilities in handling sequential and time-series data, which are common characteristics in power grid operation. Additionally, we recognize the significance of data quantity in training robust machine learning models. To ensure improved accuracy and generalization, we will focus on enhancing our dataset from a small-scale dataset to a large-scale one. By incorporating more data instances, our ensemble model will gain better insights into the underlying patterns and relationships, leading to more accurate predictions of power grid component states during extreme weather events.

Furthermore, we also plan to explore the application of a dual hesitant fuzzy sets-based methodology for prioritizing zero-emission last-mile delivery (LMD) solutions in the context of smart grid resiliency, inspired by the research in [46]. Future work will expand the feature set used in our model to include additional relevant attributes that might impact the state of power grid components. These may include historical maintenance records, past system performance during similar weather conditions, and real-time sensor data from various grid components. By incorporating these diverse features, our ensemble model will have a more comprehensive understanding of the power grid's behavior, further improving its resilience and adaptability to various weather scenarios. We also aim to evaluate the ensemble model's performance under different geographical and climatic conditions. We can ensure the model's robustness and applicability in different settings by considering various regions with diverse weather patterns and system configurations. Our future work will focus on employing advanced machine learning techniques, increasing dataset size, and enriching the feature set to further enhance the accuracy and reliability of our ensemble classification model. By addressing these aspects, we aim to contribute to developing a more resilient and efficient power grid capable of withstanding and responding to extreme weather events with greater precision and effectiveness.

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