



A Machine Learning-Based Early Warning System For Electricity Outage Due to Extreme Weather

Helmy Satria Martha Putra^{1,2}✉, Alit Kesatria Mendala^{1,2}, Intan Jelita Saragih^{1,2}, Neng Ayu Herawati^{1,3}, Ayu Purwarianti^{1,3}, Nugraha Priya Utama^{1,3}

¹Department of Electrical Engineering and Informatics, Institut Teknologi Bandung, Indonesia, 40116

²PT PLN (Persero), Indonesia

³Center of Excellence for AI: Computer Vision, NLP, and Big Data Analytics, Institut Teknologi Bandung, Indonesia, 40116

✉ 23524018@std.stei.itb.ac.id

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Abstract

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Electricity is a critical resource that supports various sectors in Indonesia, especially during extreme weather. Outages have become serious for operational risks during extreme weather. This study proposes a machine learning-based early warning system to predict electricity outages caused by extreme weather. Historical weather and outage data were combined using spatial alignment. Key innovation of this study involved geospatial feature enrichment via HDBSCAN, Yeo-Johnson transformation, robust scaling, and class resampling using SMOTE, ADASYN, and SMOTE-ENN. Four ensemble classification models (Random Forest, XGBoost, AdaBoost, and LightGBM) were evaluated. LightGBM with SMOTE yielded the highest recall (0.99) and the fewest false negatives. These findings suggest a solution for a proactive early warning system risk mitigation in electricity under extreme weather conditions.

Keywords: *Classification, Early Warning System, Electricity Outage, Extreme Weather*

Abstrak

Listrik merupakan sumber daya krusial yang menunjang berbagai sektor di Indonesia, terutama saat menghadapi cuaca ekstrem. Gangguan listrik telah menjadi risiko operasional serius selama periode cuaca ekstrem. Penelitian ini mengusulkan sistem peringatan dini berbasis machine learning untuk memprediksi gangguan listrik akibat cuaca ekstrem. Inovasi utama dalam studi ini terletak pada pengayaan fitur geospasial menggunakan HDBSCAN, transformasi Yeo-Johnson, penskalaan robust, serta penyeimbangan kelas menggunakan SMOTE, ADASYN, dan SMOTE-ENN. Empat model klasifikasi ensemble dievaluasi. Model LightGBM dengan metode SMOTE menghasilkan nilai recall tertinggi (0,99) dan jumlah false negatif paling sedikit. Temuan ini menawarkan solusi sistem peringatan dini yang proaktif untuk mitigasi risiko gangguan listrik akibat kondisi cuaca ekstrem.

Kata-kata kunci: *Cuaca Ekstrem, Gangguan Kelistrikan, Klasifikasi, Sistem Peringatan Dini*



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1. Introduction

The demand for electricity due to economic development is increasing. As the foundation of energy for society, the electric power system is an important need [1]. The lives of the population, the majority of Indonesians use electricity to support their daily lives. The electricity supply must be maintained and safe. There are two factors that cause power outages. These include internal factors such as operational errors and external factors such as extreme weather [2].

Power outages due to extreme weather conditions are external factors that are becoming very problematic. Electrical equipment exposed to prolonged extreme weather may deteriorate in condition, potentially leading to distribution outages. Therefore, early monitoring of meteorological-related disturbances is essential to enhance prevention and mitigation efforts, ensuring the stability of the power grid. Sudden occurrences triggered by extreme weather events and their widespread impacts pose a serious threat to the operational stability of the electricity network [3].

The challenge faced by electric utilities is the absence of a system that allows teams to proactively detect disturbances by utilizing predictions of network disturbances due to extreme weather conditions [4]. Most existing systems remain reactive in nature, lacking integration between weather data and power grid data. Currently, power grid condition monitoring is conducted reactively, only after disturbances have occurred. Therefore, a data-driven early warning approach is required to integrate meteorological variables with historical grid data, enabling more accurate disturbance predictions. To address these challenges, machine learning can be applied to improve the ability to predict and warn of network disruptions by analyzing and exploring the intrinsic correlation between extreme weather and network equipment operations [5].

Machine learning can be used to accurately map extreme weather outage predictions [6]. The mapping algorithm employed is the hierarchical density-based spatial clustering algorithm, HDBSCAN. HDBSCAN outperforms standard clustering methods such as K-Means [7]. HDBSCAN has also been applied in previous studies and utilizes the Haversine formula to measure geographical distances. Therefore, HDBSCAN and Haversine can be used as a geographical approach.

Machine learning algorithms can also be utilized in addressing complications of several problems, including those in the electricity grid, such as forecasting and risk analysis [8]. In the current era of machine learning, the electric utility sector is at the forefront of a transformative evolution in outage management. Machine learning models can accurately predict power grid disruptions through a variety of modeling approaches. Based on research, common modeling challenges include tabular data, large-scale datasets, and missing values. These models are also known to provide high accuracy. Among them are Random Forest, Extreme Gradient Boosting (XGBoost), AdaBoost, and LightGBM. These models are also known to provide high accuracy, several models are Random Forest, Extreme Gradient Boosting (XGBoost), AdaBoost, and LightGBM [9].

One study focused on predicting power grid disruptions in the electric utilities case study. The prediction results from the study showed that XGBoost with MRMR and Random Forest with MRMR were the models with the best performance. XGBoost outperformed Random Forest and other models in the study [10]. Both models are considered suitable ensemble learning models for this case study and are effective [11].

One of the challenges in power outage data is the presence of numerical features that are non-Gaussian and skewed. This condition can hinder the performance of machine learning models. This makes the results not good. Therefore it is necessary to first change the features to be more normal [12]. One widely used transformation is the Yeo-Johnson transformation. Yeo-Johnson can be used for both positive and negative data, unlike Box-Cox, which is only for positive values [13],[14]. Previous research has also examined practical methods of strong transformation of outliers. The method that is considered strong is Yeo-Johnson, considering positive and negative values [15].

The transformed dataset will be scaled using Robust Scaling to detect outliers. The outlier algorithm is sometimes difficult to interpret because it assigns an outlier score to each observation in the data, to determine where the level of observation is an outlier, so that outlier probability needs to be done [16]. This is addressed by proposing a scaling method to calculate outlier probability. The outlier handling method used is robust scaler because it is strong against outliers.

The issue of imbalanced data is also one of the challenges in handling power outage data. Imbalanced data cannot be properly addressed, which leads to biased predictions and reduced

model effectiveness [17]. In the classification case study, there are several unbalanced data sets, this is a very complicated matter [18]. As data grows larger, class imbalance is often found, where one class dominates another class [19]. The class that dominates another class can usually affect the classification [20]. In classes that have small data, they are called minor classes, and vice versa, they are called major classes [21].

Imbalanced data handling used includes: SMOTE (Synthetic Minority Oversampling Technique). This technique uses the minority class as a point, then identifies and creates a K-nearest neighbour line. The points between these lines are called synthetic observations. The default value of k is 5, but it can be adjusted. This affects the original class distribution of the minority class. ADASYN (Adaptive Synthetic Sampling Approach) produces synthetic observations based on weighting [22]. SMOTE ENN is a combination of SMOTE with Edited Nearest Neighbors (ENN). ENN in SMOTE is used to refine the data set by removing ambiguous data from the majority and minority classes. Especially data that is misclassified by the nearest neighbors [23]. This study uses data imbalance handling techniques with the SMOTE, ADASYN, and SMOTE ENN techniques. When compared between SMOTE and ADASYN, the more accurate result is ADASYN [22], while SMOTE with SMOTEENN the more accurate result is SMOTEENN [24]. Furthermore, before evaluating the model for predicting power grid disruptions, first using 5-fold cross-validation and GridserachCV [25].

The classification model built is more accurate, because it utilizes several methods, geographic location, and weather or meteorological conditions to improve accuracy. This model was developed using a case study that utilizes historical data of power outages at an Indonesian electricity company. Before discussing the technical aspects of this study, it is important to highlight the contributions, objectives and novelties in the study:

1. The machine learning algorithm model for predicting power outages produces an accuracy percentage of 94% using historical real data of an Indonesian electricity company, outperforming the previous method with an accuracy of 85.67% on a different data set, offering an improvement of around 8.33%.
2. This study uses one of the best algorithms, namely the HDBSCAN, Random Forest and SMOTE algorithms simultaneously to build a model that can predict power outages. Configure the Random Forest hyperparameters by determining the max depth and n_estimator.

3. Introduce the Yeo-Johnson transformation approach to overcome the problem of class imbalance in historical power outage data, which was not done in previous studies. The Yeo-Johnson transformation approach contributes significantly to predictive accuracy.
4. Investigation of several learning algorithms such as Random Forest, XGBoost, AdaBoost, LGBM and data resampling techniques such as SMOTE, ADASYN, and ENN-SMOTE to select the best model based on the evaluation results.
5. The research aims to be utilized by electricity companies in Indonesia in taking proactive actions in anticipating power outages due to extreme weather.

The research conducted explores several forms of machine learning models from literacy exploration and direct testing, explains the methodology in the research, and the results of the analysis. Discussion of research developments for future research that utilizes power outages due to extreme weather.

2. Method

This research implemented a machine learning workflow consisting of data collection, data understanding, data preprocessing, modeling and evaluation [10] which shown in **Figure 1**. The main objective is to classify whether electrical outage will be occur based on weather conditions using ensemble learning models.

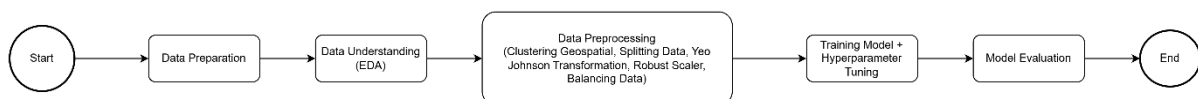


Figure 1. Electricity Weather Prediction Workflow

2.1. Data

This study begins with the data collection phase, which gathers two primary datasets. The first is weather data collected from openmeteo API which includes some meteorological features such as weather_code, temperature_2m_max, temperature_2m_min, apparent_temperature_max, apparent_temperature_min, precipitation_sum, rain_sum, snowfall_sum, precipitation_hours, sunrise, sunset, sunshine_duration, daylight_duration, wind_speed_10m_max, wind_gusts_10m_max, wind_direction_10m_dominant, et0_fao_evapotranspiration, shortwave_radiation_sum and the second one contained electrical outage data sourced from company data which indicates whether the outage occurred(1) or not(0). The variable was chosen because of it represented external factor of natural disaster. These

datasets were joined using latitude, longitude and date. The dataset contains 515842 rows and was split into training and testing sets using stratified sampling with 30% allocated to testing [10]. Descriptions of the weather variables, as presented in Table 1, were referenced from the official Open-Meteo API documentation [26].

Table 1. List of weather variables from OpenMeteo API

Variable	Unit	Description
weather_code	WMO code	The most severe weather condition on a given day
temperature_2m_max	°C (°F)	Maximum and minimum daily air temperature at 2 meters above ground
temperature_2m_min	°C (°F)	Maximum and minimum daily air temperature at 2 meters above ground
apparent_temperature_max	°C (°F)	Maximum and minimum daily apparent temperature
apparent_temperature_min	°C (°F)	Maximum and minimum daily apparent temperature
precipitation_sum	mm	Sum of daily precipitation (including rain, showers and snowfall)
rain_sum	mm	Sum of daily rain
snowfall_sum	cm	Sum of daily snowfall
precipitation_hours	hours	The number of hours with rain
sunrise	iso8601	Sun rise and set times
sunset	iso8601	Sun rise and set times
sunshine_duration	seconds	The number of seconds of sunshine per day (WMO: irradiance >120 W/m ²)
daylight_duration	seconds	Number of seconds of daylight per day
wind_speed_10m_max	km/h (mph, m/s, knots)	Maximum wind speed and gusts on a day
wind_gusts_10m_max	km/h (mph, m/s, knots)	Maximum wind speed and gusts on a day
wind_direction_10m_dominant	°	Dominant wind direction
shortwave_radiation_sum	MJ/m ²	The sum of solar radiation on a given day in Megajoules
et0_fao_evapotranspiration	mm	Daily sum of ETo Reference Evapotranspiration of a well-watered grass field

2.2. Data Understanding

After data collection phase, the next step was data understanding which aimed to explore about structure, distribution and quality of the dataset. The dataset consisted of numerical data while the target is categorical. In this phase, there were some findings about the distribution of data which can decide what transformation we should use. Additionally, this phase checked outlier of the dataset using statistical outlier and domain outlier. After that, domain validation was performed on the features. Finally, correlations among features were examined. Insight from this step informed data preparation strategies including transformation, scaling and feature selection.

2.3. Data Preprocessing

Based on the data understanding step, several preprocessing steps were applied to ensure the dataset is ready for modeling phase. For decreasing the bias of geographical, two features were measured to enrich the features. Distance to the load center and clustering was applied to enrich the features. Distance to load center calculated using Haversine which is calculated from the outage location to substation. Besides that, clustering algorithm was applied using HDBSCAN to catch the spatial location-based information [7].

Not all features were used in model training. A filter-based feature selection technique was applied based on the correlation value to the target. Features with high correlation were retained for modeling step. Features were shown highly correlated with another feature not used in the model because of multicollinearity.

Furthermore, Yeo-Johnshon transformation was applied to normalize skewness in numerical feature distribution. Yeo-Johnson was chosen because This transformation was chosen because it is suitable for data that includes both positive and negative values [13]. Robust scaling was applied to mitigate outlier impact and ensure each feature values have same scale for the next analysis [16]. This scaling method uses the interquartile range (IQR) rather than the mean and standard deviation.

Due to the high degree of imbalance in target variable, several resampling techniques were applied, including SMOTE, SMOTE-ENN, and ADASYN [22], [23]. SMOTE (Synthetic Minority Oversampling Technique) generated synthetic value for minority class by interpolating existing instance to the nearest neighbour, it will reduce overfitting. ADASYN (Adaptive Synthetic Sampling) built sampling from SMOTE which generated more synthetic data in regions when

minority class is sparsely represented or harder to learn. So, the classifier could learn about complex pattern. SMOTE ENN combines SMOTE and Edited Nearest Neighbour (ENN). This resamples technique will remove noisy samples after oversampling. It aimed to balance and clean the dataset. Each technique was evaluated individually and assessed its impact on model performance.

2.4. Modeling

In this study, four ensemble learning algorithms were proposed to classify electricity outages based on meteorological variable. The model included Random Forest, XGBoost, AdaBoost, and LightGBM. Random Forest is a classifier model that distinguishes itself by employing multiple decision trees instead of a single one. XGBoost employs a gradient boosting procedure, building trees sequentially to correct errors and optimize predictive accuracy. Random Forest and XGBoost were selected due to their well-established performance in imbalanced classification tasks. These models provide computationally efficient and practical alternatives to deep learning for small, structured datasets [27]. The AdaBoost is an algorithm which adaptively obtains the optimal weight of each weak classifier, fuses this weight into the probability of each class in each weak classifier, and then fuses it with the probability of each class in the original weak classifier [28]. Adaboost was chosen due to their proven efficacy in various classification tasks and their robustness against overfitting and class imbalance when combined with appropriate sampling techniques [29]. LightGBM is a model that constructs a robust predictive model by combining multiple weak learners, such as weak classifiers or regressors. LightGBM was selected due to its fast-training speed, low memory usage, and high classification accuracy, especially on structured datasets. Moreover, it provides native support for handling imbalanced data through class weighting and customized loss functions [30]. Each model was examined using the pre-processed and balanced dataset produced by various resampling techniques, including SMOTE, ADASYN, and SMOTE-ENN.

To ensure robust evaluation, the training process utilized stratified 5-fold cross-validation, preserving the proportion of the target classes in each fold. Some parameters were applied to model to check the performance in every fold. And the best parameter was applied to training phase with all training dataset. The method used was GridSearchCV. List of parameters used for GridSearchCV [10], [31] mentioned in Table 2.

Table 2. List of parameters

Model	Hyperparameter	Value Range
Random Forest	n_estimators	[100, 200, 300]
	max_depth	[None, 10, 20, 30]
	min_samples_split	[2, 5, 10]
	min_samples_leaf	[1, 2, 4]
XGBoost	n_estimators	[100, 200, 300]
	max_depth	[3, 5, 7]
	learning_rate	[0.01, 0.1, 0.2]
	subsample	[0.6, 0.8, 1.0]
	colsample_bytree	[0.6, 0.8, 1.0]
	gamma	[0, 0.1, 0.2]
AdaBoost	n_estimators	[50, 100, 150, 200]
	learning_rate	[0.01, 0.1, 0.2, 1.0]
LightGBM	n_estimators	[100, 200, 300]
	max_depth	[-1, 10, 20]
	learning_rate	[0.01, 0.1, 0.2]
	num_leaves	[31, 50, 100]
	min_child_samples	[10, 20, 30]

2.5. Evaluation

During the training phase, the dataset was split into training and testing subsets. The models were trained on the training set, and their performance evaluated on the test set with some classification metrics, including precision, recall, F1-score, and the confusion matrix [10]. All of the metrics above were used because the distribution of the target is imbalanced.

2.6. Deployment

The last step, the trained model was deployed in website application. The application contained interactive maps which display the warning indicator when the potential outage was predicted to occur. The input of this application was weather forecast which contains meteorological data from Openmeteo API.

3. Results and Discussion

3.1. Research Findings

This study evaluates the effectiveness of four supervised ensemble learning models, namely Random Forest, XGBoost, AdaBoost, and LightGBM (LGBM) in predicting electricity grid outages due to extreme weather in West Java. Each model was trained and tested on real operational data, using three different resampling methods (SMOTE, ADASYN, and ENN-

SMOTE) to address class imbalance. Then a performance analysis was carried out using several evaluation methods, Accuracy, Precision, Recall, Confusion Matrix, F1-Score, F1/2-Score, and F2 Score.

As part of the identification of extreme weather factors that can affect the occurrence of power grid outages, this study has conducted a correlation analysis between weather features from historical weather data obtained from OpenMeteo with historical data on power grid outages obtained from internal company records (which is used as a label). The study uses a heatmap according to **Figure 2**, and several weather features are selected that have a high value of correlation with a threshold of 0.05. These features are wind_direction_10m_dominant, shortwave_radiation_sum, et0_fao_evapotranspiration, daylight_duration, sunshine_duration, precipitation_sum, rain_sum, precipitation_hours.

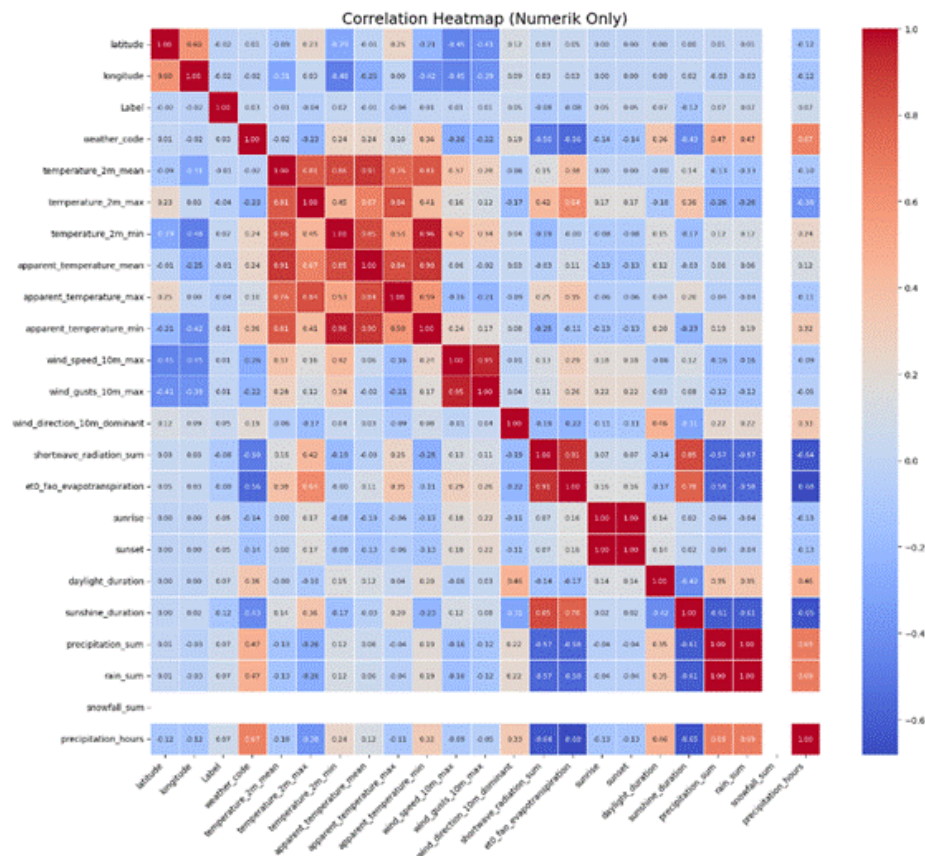


Figure 2. Correlation between weather factors and electrical outage labels

Table 3 shows that the Precision, Recall, and F1-Score values for normal conditions or no outages (Class 0) are consistently high, only the AdaBoost model provides a value of around 0.80 for recall and 0.90 for F1-Score. This indicates that the evaluated models are highly effective at

recognizing normal conditions or no outages (Class 0), almost never misclassifying normal data as outages, with precision, recall, and F1-Score values approaching 1 (100%), except for the AdaBoost model which produces more false positives than other models.

Table 3. Comparison of Precision, Recall, and F1-Score for Each Class, for All Model and Resampling Method Combinations

Model	Resampling	Precision (Class 0)	Recall (Class 0)	F1-Score (Class 0)	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)
Random Forest	SMOTE	1.00	1.00	1.00	0.91	0.97	0.94
	ADASYN	1.00	1.00	1.00	0.91	0.96	0.94
	ENN-SMOTE	1.00	1.00	1.00	0.85	0.98	0.91
XGBoost	SMOTE	1.00	1.00	1.00	0.60	0.99	0.74
	ADASYN	1.00	1.00	1.00	0.49	0.98	0.65
	ENN-SMOTE	1.00	1.00	1.00	0.57	0.99	0.72
AdaBoost	SMOTE	1.00	0.88	0.93	0.03	0.86	0.05
	ADASYN	1.00	0.87	0.93	0.02	0.71	0.04
	ENN-SMOTE	1.00	0.89	0.94	0.03	0.88	0.06
LGBM	SMOTE	1.00	1.00	1.00	0.70	0.99	0.82
	ADASYN	1.00	1.00	1.00	0.66	0.99	0.79
	ENN-SMOTE	1.00	1.00	1.00	0.70	0.99	0.82

Table 4. Comparison of Macro-Averaged Metrics, for All Model and Resampling Method Combinations

Model	Resampling	Macro Avg Precision	Macro Avg Recall	Macro Avg F1-Score
Random Forest	SMOTE	0.95	0.99	0.97
	ADASYN	0.96	0.98	0.97
	ENN-SMOTE	0.93	0.99	0.96
XGBoost	SMOTE	0.80	0.99	0.87
	ADASYN	0.74	0.99	0.82
	ENN-SMOTE	0.78	0.99	0.86
AdaBoost	SMOTE	0.51	0.87	0.49
	ADASYN	0.51	0.79	0.49
	ENN-SMOTE	0.51	0.88	0.50
LGBM	SMOTE	0.85	0.99	0.91
	ADASYN	0.83	0.99	0.90
	ENN-SMOTE	0.85	0.99	0.91

For outage conditions (Class 1), not all models show high performance score (above 0.90). When viewed from the F1-Score (Class 1), only the Random Forest model (with any resampling method) has a value above 0.90, showing its strong capability to detect real outage events. When averaged across both classes (macro average) in Table 4, Random Forest and LGBM consistently achieve macro F1-scores above 0.90, indicating balanced performance.

In addition to F1-Score, this study also measured the performance of F1/2 which emphasizes more on precision and false positive, and F2 which emphasizes more on recall and false negative. As shown in Table 5, models that have high F1/2 and F2 values above 0.90 are Random Forest and LGBM models.

Table 5. Comparison of the F1/2-score and F2-score for All Model and Resampling Method

Model	Resampling	F1/2-Score	F2-Score
Random Forest	SMOTE	0.9492	0.9587
	ADASYN	0.9443	0.9517
	ENN-SMOTE	0.9298	0.9500
XGBoost	SMOTE	0.8017	0.8712
	ADASYN	0.7204	0.8112
	ENN-SMOTE	0.7821	0.8578
AdaBoost	SMOTE	0.0714	0.1176
	ADASYN	0.0581	0.0958
	ENN-SMOTE	0.0786	0.1290
LGBM	SMOTE	0.8647	0.9131
	ADASYN	0.8410	0.8972
	ENN-SMOTE	0.8606	0.9099

Table 6. Comparison of True Negative, False Positive, False Negative, True Positive for All Model and Resampling Method

Model	Resampling	TN	FP	FN	TP
Random Forest	SMOTE	154092	58	17	586
	ADASYN	154095	55	23	580
	ENN-SMOTE	154047	103	13	590
XGBoost	SMOTE	153747	403	9	594
	ADASYN	153526	624	15	588
	ENN-SMOTE	153694	456	9	594
AdaBoost	SMOTE	135157	18993	87	516
	ADASYN	134672	19478	175	428
	ENN-SMOTE	136474	17676	71	532
LGBM	SMOTE	153899	251	8	595
	ADASYN	153846	304	9	594
	ENN-SMOTE	153892	258	9	594

In terms of the macro average values for F1, F1/2, and F2, Random Forest consistently provides the highest and most stable performance, ranging from 0.92 to 0.97 across all resampling methods used. The next best performing model is LightGBM, with macro average F1, F1/2, and F2 values ranging from approximately 0.84 to 0.91.

From **Table 6**, the model with the fewest False Negatives is the LGBM model with the SMOTE resampling method, resulting in only 8 False Negatives (missed outages), although the number of false positives is slightly higher compared to other models such as Random Forest.

3.2. Discussion

The findings indicate that ensemble-based learning models, especially Random Forest and LightGBM, are well-suited for predicting electricity outages caused by extreme weather conditions. The consistent performance of Random Forest across all metrics suggests its robustness in handling imbalanced classification problems, especially in recognizing both normal and outage events with high precision and recall.

However, from a utility company's perspective, minimizing false negatives (missed outages) is more critical than minimizing false positives. Missed outages can lead to severe consequences including unserved energy, customer blackouts, and potential financial and

reputational damage. In this regard, while Random Forest provides the best overall balance, LightGBM with SMOTE emerges as the best model due to its minimal false negative count, despite generating more false positives.

This trade-off poses a practical question: Is the company willing to accept a higher false alarm rate to avoid critical missed detections? The answer to this question depends on the company's tolerance for operational overhead versus risk exposure. This opens up a new line of research focusing on cost-benefit analysis between false negatives and false positives in outage prediction models.

The superior performance of LGBM-SMOTE can be attributed to several factors. LightGBM is particularly efficient for high-dimensional tabular datasets and excels in capturing non-linear interactions among variables. Its Gradient-based One-Side Sampling (GOSS) allows the model to concentrate on harder-to-classify samples, thus improving recall on minority classes. SMOTE, on the other hand, helps enhance the representation of outage events during training, giving the model better insight into rare cases.

Meanwhile, ADASYN and SMOTE-ENN, while performing well in certain cases, did not match the ability of SMOTE to reduce false negatives when used with LGBM. This is consistent with known limitations of ADASYN, which is sensitive to the local density of minority class samples.

The results align with existing literature stating that weather attributes such as radiation, rainfall duration, and wind direction significantly affect power grid reliability. This confirms the relevance of incorporating meteorological data into predictive maintenance systems.

Overall, the study provides practical and scientific contributions by offering a data-driven model that enhances early outage detection. The outcomes support electricity providers in allocating maintenance resources more efficiently and improving service reliability. Future work should explore integrating economic cost functions directly into model evaluation and decision thresholds, to refine the trade-offs between false alarms and missed detections in a real-world operational context.

4. Conclusion

The main contribution of this research is the identification of the most suitable algorithm and resampling method for handling highly imbalanced electricity outage data. This is achieved

by selecting the model that yields the lowest fault prediction error—particularly minimizing undetected outages (false negatives) while also identifying the most influential weather-related features that affect the risk of outages in the power grid.

This study demonstrates that ensemble learning models, especially LightGBM combined with the SMOTE resampling method, can significantly enhance the accuracy of predicting electricity grid outages caused by extreme weather conditions in West Java. The LightGBM-SMOTE combination consistently produced the lowest false negative rate, aligning well with the operational needs of the electricity company, where minimizing undetected outages is a top priority.

The most influential weather features contributing to outage risk include daylight duration, solar irradiation, total rainfall, rainfall duration, wind direction, and evapotranspiration. These findings validate the relevance of meteorological data in outage risk modeling and reinforce the importance of feature selection and preprocessing in predictive analytics.

Overall, this research confirms that integrating proper data preprocessing, appropriate resampling strategies, and robust ensemble models can significantly improve outage prediction performance on imbalanced datasets. The resulting machine learning-based early warning system has the potential to support electricity providers in optimizing resource allocation, maintenance planning, and improving grid reliability under adverse weather conditions.

Despite its contributions, this study has certain limitations. The analysis was limited to data from the West Java region and focused solely on weather-related factors, excluding other important variables such as asset condition, network density, and surrounding vegetation. Furthermore, only a limited set of models was explored.

Future research is encouraged to test the developed model in different regions across Indonesia and incorporate additional variables such as equipment age, network density, peak loads, and vegetation conditions. This expansion is expected to improve model generalization and robustness, thereby supporting broader applications in diverse environments and enhancing the overall resilience of outage prediction systems.

References

- [1] O. Majeed Butt, M. Zulqarnain, and T. Majeed Butt, "Recent advancement in smart grid technology: Future prospects in the electrical power network," Mar. 01, 2021, *Ain Shams University*. doi: 10.1016/j.asej.2020.05.004.

- [2] C. M. Furse, M. Kafal, R. Razzaghi, and Y. J. Shin, "Fault Diagnosis for Electrical Systems and Power Networks: A Review," *IEEE Sens J*, vol. 21, no. 2, pp. 888–906, Jan. 2021, doi: 10.1109/JSEN.2020.2987321.
- [3] A. M. Brockway and L. N. Dunn, "Weathering adaptation: Grid infrastructure planning in a changing climate," Jan. 01, 2020, *Elsevier B.V.* doi: 10.1016/j.crm.2020.100256.
- [4] K. Alexakis, A. Michalitsi-Psarrou, D. Papaleloudis, P. Kokkinakos, and D. Askounis, "Proactive Alerting Solution: An LSTM Model for Power Outage Forecasting in Chalki, Greece," in *Proceedings of the 30th ICE IEEE/ITMC Conference on Engineering, Technology, and Innovation: Digital Transformation on Engineering, Technology and Innovation, ICE 2024*, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/ICE/ITMC61926.2024.10794288.
- [5] P. Chang, B. Tian, G. Li, Y. Sun, and H. Gao, "Prediction of Power Grid Line Faults Under Cold Wave Weather Based on Hybrid Model of XGBoost and LSTM," in *2024 4th International Conference on Intelligent Power and Systems, ICIPS 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 400–406. doi: 10.1109/ICIPS64173.2024.10900043.
- [6] X. Wang, W. Liu, F. Ding, Y. Yao, and J. Zhao, "Preventive Power Outage Estimation Based on A Novel Scenario Clustering Strategy," in *IEEE Power and Energy Society General Meeting*, IEEE Computer Society, 2024. doi: 10.1109/PESGM51994.2024.10760283.
- [7] K. R. Saunders, A. G. Stephenson, and D. J. Karoly, "A regionalisation approach for rainfall based on extremal dependence," *Extremes (Boston)*, vol. 24, no. 2, pp. 215–240, Jun. 2021, doi: 10.1007/s10687-020-00395-y.
- [8] S. Das and B. Khan, "Synergistic Deep Learning Framework for Forecasting Power Outages," Feb. 26, 2025. doi: 10.36227/techrxiv.174058858.84414705/v1.
- [9] N. Anggraini, S. J. Putra, L. K. Wardhani, F. D. U. Arif, N. Hakiem, and I. M. Shofi, "A Comparative Analysis of Random Forest, XGBoost, and LightGBM Algorithms for Emotion Classification in Reddit Comments," *JURNAL TEKNIK INFORMATIKA*, vol. 17, no. 1, pp. 88–97, May 2024, doi: 10.15408/jti.v17i1.38651.
- [10] B. Ghasemkhani *et al.*, "Machine Learning Model Development to Predict Power Outage Duration (POD): A Case Study for Electric Utilities," *Sensors*, vol. 24, no. 13, Jul. 2024, doi: 10.3390/s24134313.
- [11] M. Abdelsattar, A. AbdelMoety, and A. Emad-Eldeen, "Advanced machine learning techniques for predicting power generation and fault detection in solar photovoltaic systems," *Neural Comput Appl*, May 2025, doi: 10.1007/s00521-025-11035-6.
- [12] J. Raymaekers and P. J. Rousseeuw, "Transforming variables to central normality," *Mach Learn*, vol. 113, no. 8, pp. 4953–4975, Aug. 2024, doi: 10.1007/s10994-021-05960-5.
- [13] A. C. Atkinson, M. Riani, and A. Corbellini, "The Box–Cox Transformation: Review and Extensions," *Statistical Science*, vol. 36, no. 2, pp. 239–255, 2021, doi: 10.1214/20-STS778.
- [14] A. Shareef, H. Taha Mohammed Ali, and A. Adil Shareef, "ON SELECTING POWER TRANSFORMATION PARAMETERS WITH THE PRESENCE OF AN OUTLIER", doi: 10.5281/zenodo.8285749.
- [15] M. Riani, A. C. Atkinson, and A. Corbellini, "Automatic robust Box–Cox and extended Yeo–Johnson transformations in regression," *Stat Methods Appt*, vol. 32, no. 1, pp. 75–102, Mar. 2023, doi: 10.1007/s10260-022-00640-7.
- [16] P. Röchner, H. O. Marques, R. J. G. B. Campello, A. Zimek, and F. Rothlauf, "Robust Statistical Scaling of Outlier Scores: Improving the Quality of Outlier Probabilities for Outliers (Extended Version)," Aug. 2024, doi: 10.1007/978-3-031-75823-2_18.
- [17] Y. Han and I. Joe, "Enhancing Machine Learning Models Through PCA, SMOTE-ENN, and Stochastic Weighted Averaging," *Applied Sciences (Switzerland)*, vol. 14, no. 21, Nov. 2024, doi: 10.3390/app14219772.
- [18] F. Ahmed and R. Shamsuddin, "A comparative study of credit card fraud detection using the combination of machine learning techniques with data imbalance solution," in *Proceedings - 2021 2nd International Conference on Computing and Data Science, CDS 2021*, Institute of Electrical and Electronics Engineers Inc., Jan. 2021, pp. 112–118. doi: 10.1109/CDS52072.2021.00026.
- [19] A. M. Halim, M. Dwifabri, and F. Nhita, "Handling Imbalanced Data Sets Using SMOTE and ADASYN to Improve Classification Performance of Ecoli Data Sets," *Building of*

- Informatics, Technology and Science (BITS)*, vol. 5, no. 1, Jun. 2023, doi: 10.47065/bits.v5i1.3647.
- [20] X. Jiang and Z. Ge, "Data Augmentation Classifier for Imbalanced Fault Classification," *IEEE Transactions on Automation Science and Engineering*, vol. 18, no. 3, pp. 1206–1217, Jul. 2021, doi: 10.1109/TASE.2020.2998467.
- [21] K. Umam Syaliman, "<http://infor.seaninstitute.org/index.php/infokum/index> INFOKUM is licensed under a Creative Commons Attribution-Non Commercial 4.0 International License (CC BY-NC 4.0) ENHANCE THE ACCURACY OF K-NEAREST NEIGHBOR (K-NN) FOR UNBALANCED CLASS DATA USING SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE (SMOTE) AND GAIN RATIO (GR)," *JURNAL INFOKUM*, vol. 10, no. 1, 2021, [Online]. Available: <http://infor.seaninstitute.org/index.php/infokum/index>
- [22] D. Salifu, L. Chepkemoui, E. A. Ibrahim, K. Nkoba, and H. E. Z. Tonnang, "Data Augmentation and Machine Learning algorithms for multi-class imbalanced morphometrics data of stingless bees," *Heliyon*, vol. 11, no. 3, p. e42214, 2025, doi: <https://doi.org/10.1016/j.heliyon.2025.e42214>.
- [23] R. Bounab, K. Zarour, B. Guelib, and N. Khelifa, "Enhancing Medicare Fraud Detection Through Machine Learning: Addressing Class Imbalance With SMOTE-ENN," *IEEE Access*, vol. 12, pp. 54382–54396, 2024, doi: 10.1109/ACCESS.2024.3385781.
- [24] G. Husain *et al.*, "SMOTE vs. SMOTEENN: A Study on the Performance of Resampling Algorithms for Addressing Class Imbalance in Regression Models," *Algorithms*, vol. 18, no. 1, Jan. 2025, doi: 10.3390/a18010037.
- [25] Z. M. Alhakeem, Y. M. Jebur, S. N. Henedy, H. Imran, L. F. A. Bernardo, and H. M. Hussein, "Prediction of Ecofriendly Concrete Compressive Strength Using Gradient Boosting Regression Tree Combined with GridSearchCV Hyperparameter-Optimization Techniques," *Materials*, vol. 15, no. 21, Nov. 2022, doi: 10.3390/ma15217432.
- [26] Open-Meteo.com, "Weather Forecast API," Open-Meteo.com.
- [27] M. Imani, A. Beikmohammadi, and H. R. Arabnia, "Comprehensive Analysis of Random Forest and XGBoost Performance with SMOTE, ADASYN, and GNUS Under Varying Imbalance Levels," *Technologies (Basel)*, vol. 13, no. 3, Mar. 2025, doi: 10.3390/technologies13030088.
- [28] W. Shan, D. Li, S. Liu, M. Song, S. Xiao, and H. Zhang, "A random feature mapping method based on the AdaBoost algorithm and results fusion for enhancing classification performance," *Expert Syst Appl*, vol. 256, Dec. 2024, doi: 10.1016/j.eswa.2024.124902.
- [29] W. Tao, Z. Sun, Z. Yang, B. Liang, G. Wang, and S. Xiao, "Transformer fault diagnosis technology based on AdaBoost enhanced transferred convolutional neural network," *Expert Syst Appl*, vol. 264, Mar. 2025, doi: 10.1016/j.eswa.2024.125972.
- [30] S. Meng, Z. Shi, C. Xia, C. Zhou, and Y. Zhao, "Exploring LightGBM-SHAP: Interpretable predictive modeling for concrete strength under high temperature conditions," *Structures*, vol. 71, Jan. 2025, doi: 10.1016/j.istruc.2024.108134.
- [31] E. Lodhi, F. Y. Wang, G. Xiong, A. Dilawar, T. S. Tamir, and H. Ali, "An AdaBoost Ensemble Model for Fault Detection and Classification in Photovoltaic Arrays," *IEEE Journal of Radio Frequency Identification*, vol. 6, pp. 794–800, 2022, doi: 10.1109/JRFID.2022.3212310.