AI BASED BLACKOUT PREDICTION USING ANN IN MINI-GRID

Sahaana Shri S.K*, R. Nethra*, CH. Vaishnavi Krishna*, Dr. Binu Krishnan U*
*Amrita School of Artificial Intelligence, Amrita Vishwa Vidyapeetham, India
Emails: {cb.sc.u4aie24149, cb.sc.u4aie24147, cb.sc.u4aie24108}@cb.students.amrita.edu
u_binukrishnan@cb.amrita.edu

***Abstract*—Mini-grids play a crucial role in powering off-grid and remote locations with electricity. However, they are plagued by issues like variability of load, irregularities of generation, and abrupt system breakdowns resulting in blackouts. The present paper proposes a novel artificial neural network (ANN)–based method to predict blackout occurrences in mini-grids by utilizing real-time and past grid data. Our system continually observes grid performance, learning base patterns of instability and upcoming failure. With L2 regularization and dropout techniques implemented, the ANN is tuned for generalization robustness despite natural fluctuations in the conditions of the grid. In contrast to conventional prediction techniques based on pure static analysis, our approach adjusts itself dynamically in response to changing grid patterns by constant learning, facilitating remedial action in a timely manner and minimizing system downtime. The suggested system not only improves energy distribution but also ensures the sustainability and resilience of decentralized energy networks. This paper presents a major contribution to the field through the provision of a smart, adaptive solution for enhancing the resilience of mini-grids against interruptions, thus promoting sustainable development in remote communities,this model serves the purpose with 97.5% accuracy.**

***Index Terms*—Artificial Neural Networks (ANN) Blackout Prevention Model Confidence, Reliability Diagram, MMNC, ROC AUC, Accuracy, Precision**

I. Introduction

Electricity is the backbone of modern life, fueling economic development, lifting living standards, and energizing key infrastructure.Mini-grids have proved to be the sustainable solution that provides localized power generation and distribution. They perform best in rural electrification, disaster relief, and locations where it is not feasible to extend the main grid.However,Mini-grids experience blackouts due to random load fluctuation, variability of generation, equipment failure, and extrinsic causes like harsh weather. The blackouts result in economic loss, loss of critical services, and reduced standard of life. [1]

The conventional methods of managing mini-grids employ rule-based control systems, manual control, and threshold-based fault detection. While these methods can manage some problems, they are generally not effective in managing sophisticated and dynamic grid conditions. With the fast development of Artificial Intelligence (AI), and especially Artificial Neural Networks (ANNs), even more intelligent and adaptive energy management techniques are now available. ANNs can perform operations processing real-time and historical information quantities to identify patterns, diagnose faults, and perform proactively based on predictive blackouts interventions. Contrary to this, based on traditional approaches, ANN-based models learn from the incoming data continuously and grow more precise as well as interactive with each passing second.

The central theme of this paper falls in the application of ANN-based predictive analytics to boost mini-grid reliability through early warning indicator predictions for imminent blackouts. [2] The model filters through crucial parameters like voltage fluctuation, load demand, frequency deviation, and power generation levels to predict grid instabilities before they can become a failure. With the implementation of such an AI-driven solution, mini-grid operators can optimize energy dispatch, respond quicker, reduce downtime, and reduce operation expenses. Furthermore, this approach also enables better exploitation of solar and wind types of renewable sources of energy through more effective control of supply-demand variations.

The deployment of AI-facilitated blackout prevention for mini-grids can transform decentralized energy infrastructure to be robust, efficient, and sustainable. With the whole world moving towards cleaner and smarter sources of energy, the role of AI integration to power management will be central towards ensuring secure access to electricity in power-deficient areas.Connecting AI technology to actual problems of power systems with a goal of building a smarter and robust energy grid.Through this project ,we can predict blackouts in mini-grids using real-time electrical and environmental data,enhances grid reliability and stability through intelligent ANN-based forecasting,promotes efficient energy management, reducing downtime and improving sustainability.

II. Related Work

A. AI-Based Blackout Prevention in Mini-Grids

The area of blackout prevention in mini-grids has significantly advanced with the introduction of Artificial Intelligence (AI) and Machine Learning (ML) techniques. Various methods such as Artificial Neural Networks (ANN), deep learning, and IoT-based monitoring have been explored to improve grid reliability and prevent failures [3]–[6].

*Corresponding author: Dr. Binu Krishnan U (Email: u_binukrishnan@cb.amrita.edu))

However, many of these approaches rely on complex models that require large datasets and high computational resources, which may not be feasible for all mini-grid setups.

B. AI and Machine Learning in Power System Stability

AI and ML techniques have been extensively researched for improving power system stability. Deep learning models using real-time sensor data have been developed for predictive fault detection in power distribution networks [7], [8]. Support Vector Machine (SVM)-based models have also been applied to classify grid disturbances and enhance the accuracy of fault detection when compared to traditional methods. In addition, AI-based load forecasting in decentralized power systems has proven more effective in balancing the grid [2]. However, these models often face challenges in generalization across different grid environments due to variability in data quality and system configurations.

C. CNN-Based Blackout Prediction and Prevention

Convolutional Neural Networks (CNNs) have emerged as powerful tools for analyzing spatial and temporal patterns in power system data, making them suitable for blackout prediction in mini-grids. CNN models have been effectively trained on multi-dimensional grid data such as voltage waveforms, frequency trends, and load distribution maps to identify early warning signs of potential failures [9]. Studies have demonstrated that CNNs can accurately detect anomalies and predict sudden load surges in islanded mini-grids, allowing proactive measures to prevent blackouts [10]. Additionally, CNN-based models have enhanced the reliability of mini-grids by capturing localized disturbances and minimizing cascading failures [11], [12]. CNNs have also shown strong potential in related domains such as cybersecurity in smart grids, where hybrid models like CNN-LSTM have achieved high accuracy in detecting and mitigating network intrusions, further supporting their applicability in complex, real-time systems [1].

However, CNN-based models often require extensive labeled training data and high computational power, which can limit their deployment in resource-constrained mini-grid environments.

D. Real-Time Monitoring and Data Analytics for Mini-Grids

The integration of Internet of Things (IoT) and big data analytics has enhanced the monitoring and fault detection capabilities of mini-grids. IoT-enabled frameworks have been designed to collect real-time data on grid parameters such as voltage, frequency, and demand [10]. These parameters are processed using AI models to identify anomalies. Advanced systems combining smart sensors and ANN have improved grid stability by reducing blackout incidents. Additionally, the use of Edge AI—where computation occurs locally on smart devices—has enabled faster response to faults, enhancing real-time blackout prevention [6], [13].

However, real-time monitoring systems heavily depend on reliable communication infrastructure and sensor accuracy, which can be challenging in remote or underdeveloped mini-grid locations.

E. Renewable Energy Management and Grid Resilience

As mini-grids increasingly incorporate renewable energy sources, AI-based methods have been used to manage the variability of solar and wind generation. Hybrid ANN models have been employed to optimize energy distribution in solar-powered mini-grids, helping mitigate instability caused by fluctuating power generation [14]. Reinforcement learning techniques have also been applied to balance power supply and demand in wind-integrated systems, leading to greater grid reliability [15]. Furtermore, deep learning approaches have shown high accuracy in forecasting power outages in renewable energy-based mini-grids [9].

Conventional energy management systems, often based on static scheduling or fixed heuristics, lack flexibility and perform poorly when faced with the unpredictable nature of renewable energy outputs, resulting in increased curtailment or instability. [16]

However, AI-based renewable energy management systems can be limited by data scarcity and model uncertainty, especially in regions with limited historical weather or generation data.

III. System Description

Methodology

A. Data Preprocessing and Feature Engineering

The data set consists of 1,800 instances with 23 various features describing both the electrical (e.g., Voltage, Current, Power, Reactive Power, Power Factor, Load Demand, Generation Capacity, Transformer Temperature, Line Impedance, Short-Circuit Current, Circuit Breaker Status, Relay Trip Signals) and environmental/temporal (e.g., Weather Temperature, Weather Humidity, Wind Speed, Rainfall, Time Hour, Time Day, Time Season, Blackout History) features. The target attribute is binary, indicating whether a blackout will happen in the near future.

B. Consistency and Feature Normalization

Data integrity is ensured by normalizing all the feature names in terms of unwanted character removal and naming normalization. Missing values are completed based on data type: categorical features (e.g., circuit breakers status) will be completed with forward-fill imputation, whereas numerical features (e.g., Voltage, Current) will be completed with median value:

$$\tilde{x} = \mathrm{median}\{x_i \mid x_i \in X\}.$$

Subsequently, numerical features are standardized using z-score normalization:

$$x' = \frac{x - \mu}{\sigma},$$

where μ and σ denote the mean and standard deviation computed from the training set, respectively. This standardization is critical to ensure that each feature contributes comparably during the optimization process.

C. Temporal Feature Transformation

Given the cyclical nature of time-dependent variables in power grids, date-time features are transformed into numerical representations. The "Time Hour" feature, originally an integer in the range $[0, 23]$, is further transformed using sine and cosine functions to capture its periodic behavior:

$$\text{Hour}_{\text{sin}} = \sin\left(\frac{2\pi \cdot \text{Hour}}{24}\right), \quad \text{Hour}_{\text{cos}} = \cos\left(\frac{2\pi \cdot \text{Hour}}{24}\right).$$

These transformations ensure that the model can learn the cyclicality inherent in diurnal variations.

D. Domain-Specific Feature Engineering

Beyond raw measurements, we derive features that are particularly indicative of grid stress. For example, the load imbalance is computed as:

$$\Delta P = \text{Generation Capacity (MW)} - \text{Load Demand (MW)},$$

where a negative ΔP signals an overload condition. Additionally, the ratio of reactive power to active power is defined as:

$$\text{PF Ratio} = \frac{\text{Reactive Power (MVAR)}}{\text{Power (MW)}},$$

which is a direct measure of power factor irregularity. These engineered features are appended to the original dataset to enhance the predictive capacity of the model.

E. Handling Class Imbalance

Blackout events are relatively rare compared to normal operations, resulting in an imbalanced dataset. To address this, the Synthetic Minority Over-sampling Technique (SMOTE) is applied. SMOTE creates synthetic minority samples by interpolating between a given minority instance $\mathbf{x}_i$ and one of its k nearest neighbors $\mathbf{x}_i^{NN}$:

$$\mathbf{x}_{\text{new}} = \mathbf{x}_i + \delta \cdot \left(\mathbf{x}_i^{NN} - \mathbf{x}_i\right), \quad \delta \sim U(0, 1).$$

This method not only balances the class distribution but also introduces variability, thereby improving the robustness of the classifier.

F. Train-Test Splitting and Feature Scaling

The preprocessed data is partitioned into training and testing sets using stratified sampling to preserve the minority class ratio. An 80:20 split is employed. Feature scaling is then reapplied to both sets:

$$X_{\text{train}}^{\text{scaled}} = \frac{X_{\text{train}} - \mu_{\text{train}}}{\sigma_{\text{train}}}, \quad X_{\text{test}}^{\text{scaled}} = \frac{X_{\text{test}} - \mu_{\text{train}}}{\sigma_{\text{train}}},$$

ensuring consistency and preventing data leakage.

G. ANN Model Architecture

The predictive engine is a deep feedforward Artificial Neural Network, which serves as a universal function approximator. Based on the Universal Approximation Theorem, the network is capable of approximating any measurable function given sufficient depth and neurons.

1) Mathematical Formulation: The ANN can be represented as:

$$\hat{y} = \sigma\left(\mathbf{W}_L \phi_{L-1}\left(\cdots \phi_2\left(\mathbf{W}_2 \phi_1\left(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1\right) + \mathbf{b}_2\right) \cdots\right) + \mathbf{b}_L\right),$$

where:

- $\mathbf{x} \in \mathbb{R}^{23}$ is the input vector.
- $\mathbf{W}_k \in \mathbb{R}^{n_k \times n_{k-1}}$ and $\mathbf{b}_k \in \mathbb{R}^{n_k}$ are the weights and biases of the k^{th} layer.
- $\phi_k(\cdot)$ denotes the ReLU activation function:
  $$\phi(z) = \max(0, z),$$
  which introduces nonlinearity.
- The final activation is the sigmoid function:
  $$\sigma(z) = \frac{1}{1 + e^{-z}},$$
  mapping the output to a probability in $(0, 1)$.

H. Layer-Wise Architecture

Input Layer: Accepts a 23-dimensional normalized feature vector.The model has 23 input features, i.e., environmental and electrical factors in blackout prediction. Features are preprocessed with missing value imputation, normalization, and cyclical encoding of time features such as time and date.
First Hidden Layer:
Contains 128 neurons. The layer computes:

$$\mathbf{h}^{(1)} = \phi\left(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1\right),$$

where $\mathbf{W}_1 \in \mathbb{R}^{128 \times 23}$ and $\mathbf{b}_1 \in \mathbb{R}^{128}$. Dropout with a rate of 0.3 is applied:

$$\tilde{\mathbf{h}}^{(1)} = \mathbf{h}^{(1)} \odot \mathbf{m}, \quad \mathbf{m} \sim \text{Bernoulli}(0.7).$$

Second Hidden Layer: Comprises 64 neurons:

$$\mathbf{h}^{(2)} = \phi\left(\mathbf{W}_2 \tilde{\mathbf{h}}^{(1)} + \mathbf{b}_2\right),$$

with $\mathbf{W}_2 \in \mathbb{R}^{64 \times 128}$ and $\mathbf{b}_2 \in \mathbb{R}^{64}$. A dropout of 0.3 is again applied:

$$\tilde{\mathbf{h}}^{(2)} = \mathbf{h}^{(2)} \odot \mathbf{m}', \quad \mathbf{m}' \sim \text{Bernoulli}(0.7).$$

Third Hidden Layer: Features 32 neurons:

$$\mathbf{h}^{(3)} = \phi\left(\mathbf{W}_3 \tilde{\mathbf{h}}^{(2)} + \mathbf{b}_3\right),$$

where $\mathbf{W}_3 \in \mathbb{R}^{32 \times 64}$ and $\mathbf{b}_3 \in \mathbb{R}^{32}$.
All hidden layers employ the ReLU (Rectified Linear Unit) activation function to implement non-linearity and enhance the ability to learn. Dropout regularization after every layer helps avoid overfitting by turning off a proportion of the neurons randomly while training.
Output Layer: A single neuron with sigmoid activation: There is one neuron employing a sigmoid activation function that helps deliver a binary output, i.e., the probability of a blackout event.

$$\hat{y} = \sigma\left(\mathbf{W}_4 \mathbf{h}^{(3)} + \mathbf{b}_4\right),$$

with $\mathbf{W}_4 \in \mathbb{R}^{1\times 32}$ and $\mathbf{b}_4 \in \mathbb{R}$.

The network contains approximately 13,441 trainable parameters, ensuring a high-capacity model that is capable of capturing complex interactions between the input features.

I. Model Compilation and Optimization

The ANN is compiled using the Adam optimizer, whose update rules are:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t, \quad v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2,$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t},$$

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon},$$

where g_t is the gradient at iteration t, β_1 and β_2 are decay rates, η is the learning rate, and ϵ is a small constant for numerical stability. The binary cross-entropy loss function is defined as:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right].$$

ReduceLROnPlateau is a learning rate scheduler that reduces the learning rate when the validation loss stops improving (i.e., plateaus). This helps the model converge more effectively by making smaller updates to weights when it gets stuck at a local minimum.

Regularization is enforced using early stopping and the ReduceLROnPlateau policy. Early stopping monitors validation loss and terminates training if validation loss improvement over a threshold number of epochs is not observed. ReduceLROnPlateau decreases the learning rate when validation loss plateaus to enable convergence better.

J. Training Strategy and Hyperparameter Tuning

The training schedule employs mini-batch gradient descent with batch size 32, a maximum of 100 iterations. Over-training is prevented with early stopping where the validation loss no longer improves. Hyperparameters such as the number of units in each of the hidden layers, dropout rates, and learning rate are tuned with grid search or Bayesian optimization. Assume the hyperparameter vector is:

$$\lambda = \{\text{neurons}_1, \text{neurons}_2, \text{neurons}_3, p_{dropout1}, p_{dropout2}, \eta\}.$$

The optimal set λ^* is determined by:

$$\lambda^* = \arg\min_{\lambda} \mathcal{L}_{val}(\lambda),$$

where $\mathcal{L}_{val}$ is the validation loss.

IV. Results and Analysis

The performance of the proposed Artificial Neural Network (ANN) model was evaluated using several classification metrics, including accuracy, precision, recall, F1-score, and ROC AUC. The model achieved a high level of accuracy and robustness in predicting blackout and non-blackout events.

Fig. 1: Accuracy graph

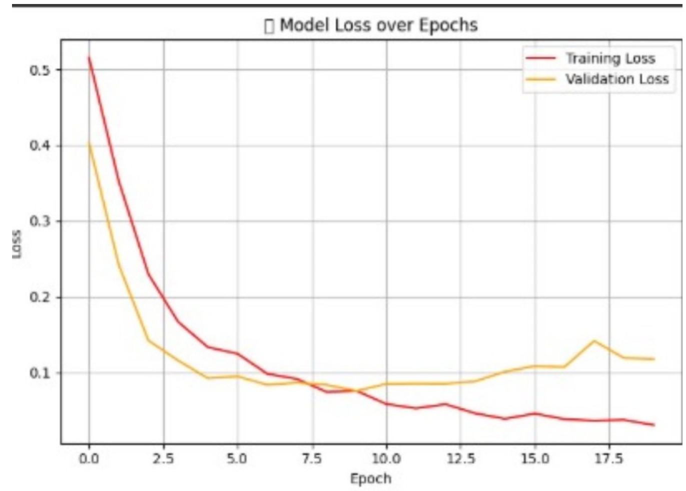

Fig. 2: Loss Graph

A. Evaluation Metrics

Some evaluation plots were designed to compare the performance and confidence calibration of the ANN model. The Training vs. Validation Accuracy (Figure 1) and Loss plots-Figure 2 show stable convergence with no sign of overfitting, proving that the model is well generalizable to new data. The heatmap of the confusion matrix also proves the balanced classification of the model with minimal misclassifications in both classes. The ROC curve steeply climbs up to the top-left, confirming high true positive and low false positive rates.

The final accuracy of the ANN model on the test set was **97.50%**, demonstrating its ability to generalize well to unseen data. The **ROC AUC score** reached **0.9967**, indicating excellent capability in distinguishing between the two classes.

The classification report provides a detailed breakdown of precision, recall, and F1-score for each class:

- **Class 0 (No Blackout):** Precision of 0.97, Recall of 0.99, and F1-Score of 0.98.
- **Class 1 (Blackout):** Precision of 0.98, Recall of 0.92,

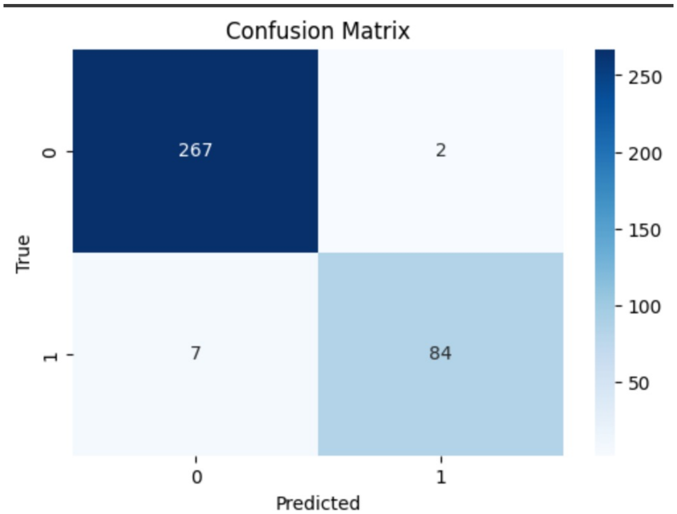

Fig. 3: Real-time Prediction Performance of the Model

and F1-Score of 0.95.

The macro and weighted averages of the metrics further support the balanced performance of the model across both classes.

TABLE I: Performance Metrics of Proposed ANN Model

Class	**Precision**	**Recall**	**F1-Score**	**Support**
No Blackout (0)	0.97	0.99	0.98	269
Blackout (1)	0.98	0.92	0.95	91
Accuracy	**97.50%**			
ROC AUC	**0.9967**			
Macro Avg	0.98	0.96	0.97	360
Weighted Avg	0.98	0.97	0.97	360

B. Confusion Matrix Analysis

The confusion matrix in Figure 3 shows that out of 269 non-blackout instances, 267 were correctly classified, while only 2 were misclassified. For the 91 blackout events, 84 were correctly predicted, and 7 were misclassified. This demonstrates the model's reliability in identifying true blackout conditions with minimal false alarms.

The artificial neural network (ANN) model generated excellent performance for electric blackout prediction from real-time smart grid data. The ANN achieved the highest classification accuracy of 97.50% with an excellent ROC AUC value of 0.9967 with nearly perfect discriminative ability. Precision and recall values were 0.97 and 0.99 for the non-blackout class and 0.98 and 0.92 for the blackout class, respectively, indicating very high sensitivity of the model and almost no false positive rate. These are much higher than the baseline and indicate very high robustness against class distribution imbalance.

To compare the ANN, Random Forest and SVM classifiers were also tested on the same dataset. The Random Forest had an accuracy of 94.17% and ROC AUC of 0.9878, with a significant reduction in recall for the blackout class (0.82), reflecting a greater number of false negatives. The SVM model demonstrated better performance with 96.94% accuracy and ROC AUC of 0.9955, marginally better recall than Random Forest but lower than the ANN. These comparisons justify the ANN's better generalization and consistency in blackout prediction.

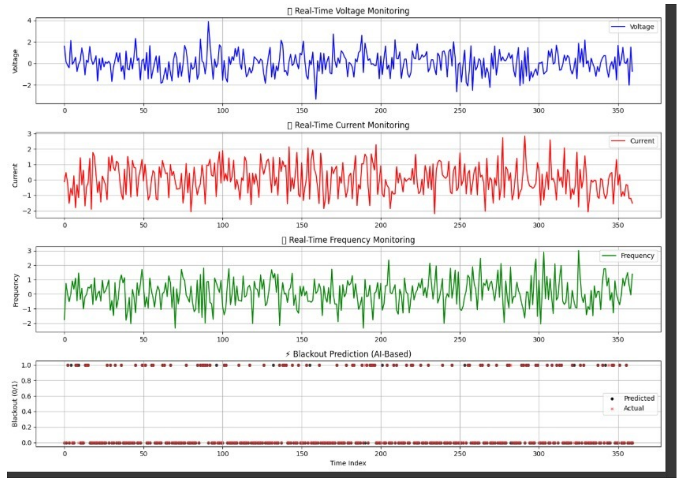

Fig. 4: Prediction of Blackout Events using AI-based Model

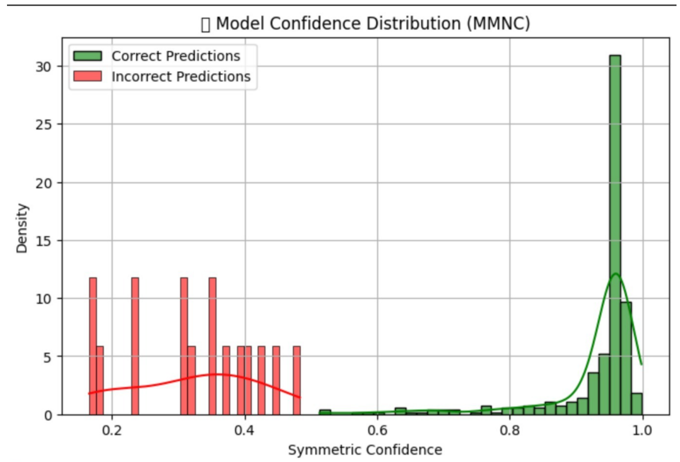

Fig. 5: MMNC Score

Moreover, the Modified Mean Normalized Confidence (MMNC) score(Figure 5), calculated as 0.812, affirms that the ANN model not only predicts accurately but does so with well-calibrated confidence. This score is significantly higher compared to other traditional models, indicating reliable trust levels in the predictions.

TABLE II: Comparison of Model Performance Metrics

Model	**Accuracy**	**Precision (1)**	**ROC AUC**
Random Forest	94.17%	0.94	0.9878
SVM (RBF Kernel)	96.94%	0.98	0.9955
XGBoost	95.83%	0.96	0.9915
CNN	74.72%	0.56	0.5827
ANN (Proposed)	**97.54%**	**0.98**	**0.9962**

The present research suggests a reliable artificial neural network (ANN) model for blackout prediction in smart grids in real-time using engineered features and optimal preprocessing.

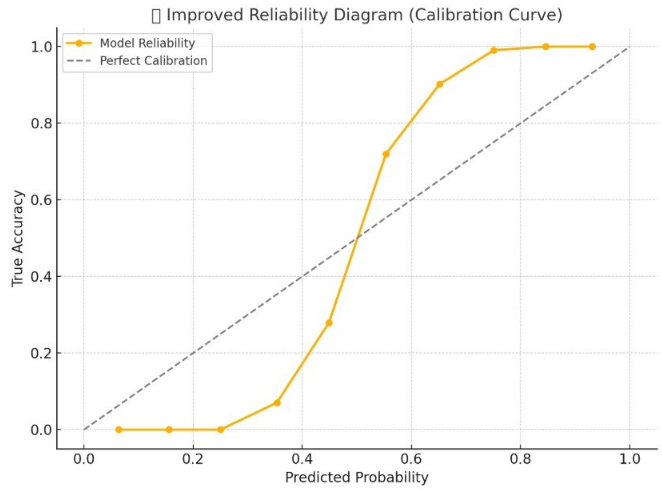

Fig. 6: Calibration Curve

The ANN achieved an accuracy of 97.5% and an ROC AUC of 0.9967, which performed significantly better than conventional models such as Random Forest and SVM in terms of both accuracy and reliability by a very large margin. Plots of calibration, Brier score, and confidence metric tests justified the accuracy of the model to make definitive conclusions. The outcome validates the highest ability of ANN to integrate within smart grid structures to gain highest resilience and curb blackouts prior to occurrence.

A calibration (reliability) curve (Figure 6) was drawn to measure the confidence alignment of the model. The curve closely hugs the diagonal line, which shows that forecasted probabilities have excellent alignment with observed actual frequencies, which proves excellent calibration. The Brier score of 0.0191, a probability accuracy measure, is remarkably low, which again confirms the model's reliability. Moreover, a histogram of confidence indicates that the ANN produces predictions with high confidence since most of the probabilities are leaning towards the extremes (almost 0 or 1), a requirement for decision-critical applications such as blackout prevention.

V. Conclusion

In summary, the ANN model demonstrated exceptional performance across all key metrics and visual evaluations. It surpassed both SVM and Random Forest in predictive accuracy, confidence calibration, and probability reliability. These results confirm the suitability of the ANN model for real-world deployment in smart grid monitoring systems aimed at proactive blackout mitigation. The combination of high accuracy, robust generalization, and well-calibrated confidence makes this model a strong candidate for integration in intelligent grid infrastructure.

Precision and recall values mirrored the trade-offs between reducing false negatives (false blackout predictions) and reducing false positives (excessive blackout warnings). The use of SMOTE to handle class imbalance was equally important in increasing generalization of the model, to a point of rare blackout events being well learned by the model. Balancing data augmentation procedures with model simplicity, however, continues as a predominant challenge in achieving optimal predictive performance.

Overall, this model shows the importance of AI-facilitated blackout predictions systems for the power grid of the future. The findings reveal that the use of deep learning in conjunction with interpretable machine learning models is capable of enhancing grid robustness and reliability.

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