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Deep Learning Proactive Approach to Blackout Prevention in Smart Grids: An Early Warning System

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Abstract

Blackout events in smart grids can have significant impacts on individuals, communities and businesses, as they can disrupt the power supply and cause damage to the grid. In this paper, a new proactive approach to an early warning system for predicting blackout events in smart grids is presented. The system is based on deep learning models: convolutional neural networks (CNN) and deep self-organizing maps (DSOM), and is designed to analyse data from various sources, such as power demand, generation, transmission, distribution and weather forecasts. The system performance is evaluated using a dataset of time windows and labels, where the labels indicate whether a blackout event occurred within a given time window. It is found that the system is able to achieve an accuracy of 98.71% and a precision of 98.65% in predicting blackout events. The results suggest that the early warning system presented in this paper is a promising tool for improving the resilience and reliability of electrical grids and for mitigating the impacts of blackout events on communities and businesses.

Keywords

Alert generation; Blackout events; Smart grids; Early warning system; Deep self-organizing map; Convolutional neural networks.

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1 Introduction

Blackouts in smart grids can have a range of negative consequences for individuals and communities. For example, blackouts can cause economic losses as businesses and households may be unable to operate or function without electricity. In addition, blackouts can disrupt essential services that are dependent on electricity, such as healthcare, communication, transportation and emergency response (Anderson & Bell, 2012). In certain situations, blackouts may also pose public safety risks, such as by disrupting traffic signals or hindering the functioning of emergency systems. Overall, blackouts can have a significant impact on the well-being and quality of life of individuals and communities. As a result, it is important to have effective tools and strategies in place to predict and prevent blackout events and to minimize their impacts on individuals and communities (Alhelou et al., 2019).

Early warning systems have the potential to enhance the resilience of smart grids by providing timely and accurate alerts of potential blackout events, allowing operators to take proactive measures to prevent or mitigate the impacts of these events (Mahzarnia et al., 2020; Zhang et al., 2017).

Smart grids are modern electricity systems that use advanced technologies to improve the efficiency, reliability and sustainability of power generation, distribution and consumption (Albasrawi et al., 2014). These systems rely on a combination of traditional and renewable energy sources, as well as digital communication and control technologies, to enable bidirectional energy flows and enable the integration of distributed energy resources (DER) such as solar panels and electric vehicles (Borlase, 2017; Tuballa & Abundo, 2016). Despite their many benefits, smart grids are also vulnerable to blackouts, which can occur due to a variety of reasons, including technical failures, natural disasters and cyber-attacks (Lázaro et al., 2021).

An early warning system has the potential to enhance the resilience of smart grids by providing timely and accurate alerts of potential blackout events, allowing operators to take proactive measures to prevent or mitigate the impacts of these events (Sharma et al., 2021). In this paper, we present a novel proactive approach to an early warning system for blackouts in smart grids, which is based on deep learning algorithms.

The motivation behind our approach lies in addressing the shortcomings of existing blackout prediction methods and enhancing the resilience of smart grids. The proposed early warning system is based mainly on the convolutional neural network (CNN) and deep self-organizing map (DSOM) deep learning models and includes four components: data collection and preprocessing, model training and prediction, alert generation and notification, and response management. It offers several key benefits. Firstly, it enables early detection and prediction of blackout events, empowering operators to take timely action to prevent or mitigate their impacts. Secondly, it aids in reducing the frequency and duration of blackouts, thereby minimizing disruptions to individuals and communities. Additionally, our system assists operators in identifying the root causes of blackout events, facilitating corrective action to prevent future occurrences.

The rest of this paper is organized as follows. The next section reviews the related literature on early warning systems for blackouts in smart grids and discusses the various techniques and approaches that have been used to develop these systems. Section 3 describes the design and implementation of the proposed early warning system. Section 4 presents the results of experiments conducted to evaluate the performance of the proposed system, including its accuracy, precision and false alarm rate. Section 5 discusses the potential challenges and limitations of the system and Section 6 concludes and outlines directions for future research and development.

2 Literature Review

Smart grid power outages can have significant negative consequences for individuals, communities and businesses, including financial losses, disrupted essential services and even public safety risks. One way to improve the resilience of smart grids is to implement early warning systems that provide timely, accurate alerts about potential blackout events. These systems allow grid operators to take proactive measures to prevent or reduce the impacts of these events (Shuai et al., 2018; Soyata et al., 2019). This literature review summarizes the state of the art in early warning systems for blackouts in smart grids and discusses the various techniques and approaches that have been used to develop these systems.

2.1 Using machine learning algorithms

One trend is the use of machine learning algorithms as a key component of early warning systems (Tomin et al., 2016). Several studies have proposed early warning systems for blackouts in smart grids based on machine learning algorithms (Gupta et al., 2015a; Gupta et al., 2015b; Khediri et al., 2020). These systems typically use real-time monitoring of grid conditions, such as voltage and current levels, to identify patterns and trends that may indicate the risk of a blackout event. For example, Gupta et al. (2015b) proposed an early warning system based on a neural network model, which is trained to predict blackout events by learning from historical data on grid conditions and events. Similarly, J. Wang et al. (2016) presented an early warning system based on support vector machine (SVM) and AdaBoost bi-level classifiers, which uses features such as voltage and current levels, as well as weather data, to predict blackout events. Another study by Yang and Li (2023) addressed the crucial task of identifying vulnerable lines in smart grid systems to enhance stability and reduce cascading fault blackouts. Employing a machine learning approach, the study proposes an identification method based on an enhanced agglomerative hierarchical clustering algorithm.

2.2 Using data analytics and real-time monitoring

Other approaches to early warning systems for blackouts in smart grids have focused on data analytics and real-time monitoring of grid conditions (Zhang et al., 2018). For example, Gupta et al. (2016) proposed a system based on a combination of data analytics and real-time monitoring, which uses an approach based on Kullback-Leibler divergence (KLD) to identify and analyse patterns in grid data and provides alerts for operators when potential blackout events are detected. Similarly, England and Alouani (2020) proposed enhancing Thevenin parameter estimation accuracy in smart grids by using individual load measurements from smart meters. They also introduced a real-time stability index to forecast instability, aiding in proactive blackout prevention. Simulations on an IEEE 30 bus power system validated the efficacy of the methods, demonstrating improved stability estimation precision and early detection of voltage instability, empowering utilities with vital tools for blackout prevention.

2.3 Using probabilistic and statistical models

In addition to the approaches mentioned above, there have also been several studies on the use of probabilistic and statistical models for early warning systems in smart grids (Rahnamay-Naeini et al., 2012; Wang et al., 2021). For example, Wang et al. (2021) proposed a system based on a probabilistic model, which used historical data on grid conditions and events to estimate the probability of a blackout event occurring in the future. Similarly, Li and Zhou (2015) presented a statistical model based on a logistic regression approach, which used data on grid conditions and events to predict the likelihood of a blackout event occurring.

2.4 Using control and optimization techniques

Other studies have focused on the use of control and optimization techniques for early warning systems in smart grids (De Zotti et al., 2018; Enacheanu et al., 2005; C. Wang et al., 2016). For example, C. Wang et al. (2016) proposed control strategies for preventing and predicting blackouts in power grids, using fast-response energy storage systems and a phase-oscillator model that considers different types of power sources and loads. The strategies can be applied to traditional and smart grids and the research offers ideas for improving the robustness and cost-efficiency of smart power grids.

Finally, there have also been several studies on the use of hybrid approaches for early warning systems in smart grids, which combine multiple techniques and approaches such as machine learning algorithms with data analytics and real-time monitoring in order to achieve improved performance and accuracy (Amroune et al., 2018; Wang et al., 2021).

Overall, the literature suggests that there is a wide range of techniques and approaches that can be used to develop early warning systems for blackouts in smart grids. These approaches include the use of machine learning algorithms, data analytics, real-time monitoring, control and optimization techniques and hybrid approaches. These approaches have been proved significant in areas of blackout prevention and resilience as the related works demonstrate. Yet, each of those techniques and approaches has its advantages and disadvantages.

Five major problem areas can be identified from the literature review (Table 1): imminent blackout prediction (P1), asset management (P2; refers to identifying problems with grid assets, such as transmission lines, transformers or generators and recommending action to prevent or mitigate these problems), cascading failure (P3), grid disturbance (P4) and risk assessment (P5; refers to helping identify potential risks to the grid, such as extreme events, e.g., natural disasters or weather hazards). In order to provide a comprehensive overview of existing research efforts in the field of smart grid management, we analyse how each study addresses specific challenges within the smart grid resilience domain.

Table 1. *Comparison of studies.*

Technique	Study	P1	P2	P3	P4	P5
Machine learning algorithms	Gupta et al. (2015b)	X	-	X	-	-
	Gupta et al. (2014)	X	-	-	X	-
	Khediri et al. (2020)	X	-	-	-	X
Data analytics and real-time monitoring	Gupta et al. (2016)	-	X	-	-	X
	England and Alouani (2020)	-	-	X	-	-
Probabilistic and statistical models	Wang et al. (2021)	-	X	-	X	-
	Li & Zhou (2015)	-	-	X	-	X
Control and optimization techniques	C. Wang et al. (2016)	X	X	-	-	-
Hybrid techniques	Amroune et al. (2018)	-	X	-	X	-
Proposed approach		X	-	X	X	X

Each of the aforementioned studies set out to address at least one of the five problems identified. This research aims to offer an approach that takes into consideration four problems: imminent blackout prediction (P1), cascading failure (P3), grid disturbance (P4) and risk assessment (P5). We structure our comparative analysis to assess how each study tackles these identified problems. By examining the methodologies, techniques and outcomes of each study in relation to these key problem areas, we aim to offer insights into the strengths and limitations of the existing approaches and identify potential avenues for further research and improvement. The suggested proactive approach, which serves as an early warning system, is described in the following section.

3 Proposed Approach

The proposed approach for an early warning system is based on the CNN deep learning model and the deep self-organizing map (DSOM). The choice of these models was based on their demonstrated effectiveness in similar tasks and their theoretical foundations. The CNN model and DSOM were selected due to their robustness in managing large datasets and their excellent generalization capabilities, which have been demonstrated in previous research (Bhatt et al., 2021). These models work together to provide highly accurate predictions of blackout events.

The system consists of five main components (Figure 1): data collection and preprocessing, the CNN model, alert generation, response management, and user interface.

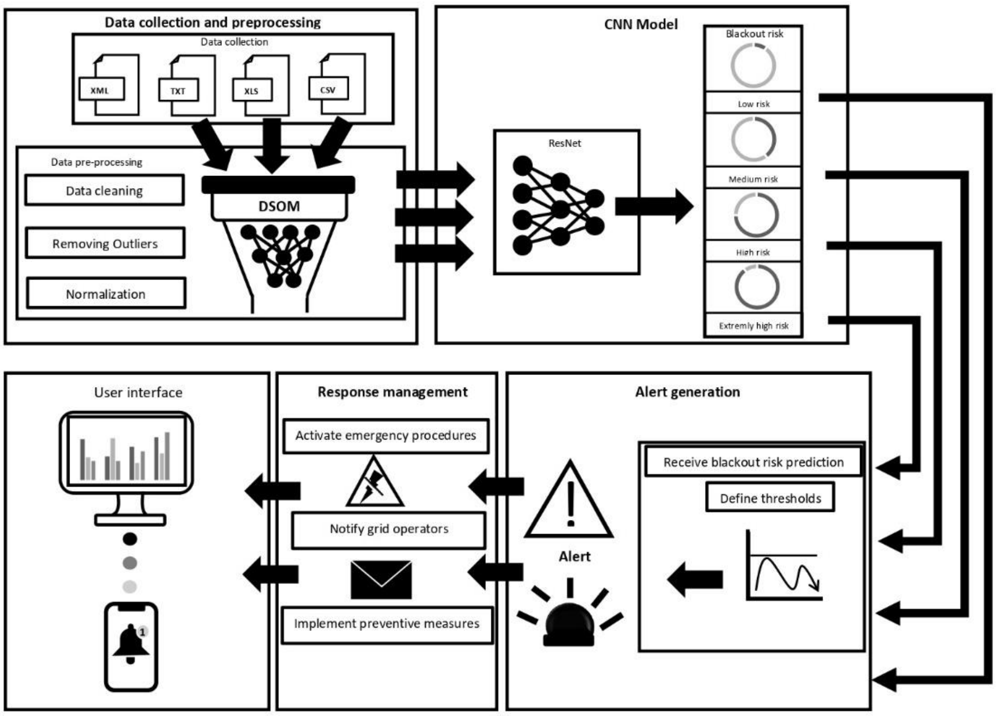

Figure 1. *Schematic overview of proposed approach.*

These components are interconnected, with data being collected and preprocessed and then fed into the CNN model for prediction. The predictions of the CNN model are then used to trigger alerts, which are sent to grid operators and used to manage the response to blackout events.

3.1 Data collection and preprocessing

This component is responsible for collecting and preprocessing data from various sources, such as real-time monitoring of grid conditions, weather forecasts and other data sources. The data are collected using sensors, meters and other monitoring devices and include information on factors such as power demand, generation, transmission, distribution and use as well as historical data. The deep self-organizing map (DSOM) is used in the data collection and preprocessing component. Its role is to analyse the data collected from various sources and identify patterns and trends that are relevant to predicting blackout events. The DSOM is used to preprocess the data, which involves removing any missing or invalid data points and normalizing and transforming the data as needed. The preprocessed data are used to create time windows, which are used as input to the CNN model. Time windows are created by dividing the data into fixed-length segments or by using techniques such as rolling windows or overlapping windows to capture trends and patterns over time.

Algorithm 1. *Data preprocessing function pseudo-code.*

```
define data_preprocessing(raw_data):
define list of relevant data fields
filter raw data to include only relevant fields
for each datapoint in raw_data:
    if datapoint is missing or invalid:
        if missing data can be filled in:
            fill in missing data
        else:
            remove invalid data
normalize data to a common scale
convert data to appropriate format for model input
return processed data
```

The data preprocessing function takes in a dataset of raw data and returns a preprocessed version of the data. It performs the following steps:

- Identify the fields of data that are relevant for the task at hand (e.g., power demand, generation, transmission, distribution).
- Filter the raw data to include only the relevant fields.
- Check for missing or invalid data points in the filtered data.
- Fill in missing data or remove invalid data as appropriate (e.g., impute missing values using the mean or median or drop rows with invalid data).
- Normalize the data to a common scale (e.g., subtract the mean and divide by the standard deviation).
- Convert the data to the appropriate format for model input (e.g., if using a self-organizing map, convert data to a matrix).
- Return the processed data.

3.2 CNN model

This component is responsible for predicting blackout events based on the time windows of preprocessed data. The convolutional neural network model is trained using a dataset of time windows and labels, where the labels indicate whether a blackout event occurred within a given time window. The CNN learns features from the data and identifies patterns and trends that are associated with blackout events. The CNN model is implemented using machine learning libraries (TensorFlow) and is trained using techniques such as gradient descent, backpropagation or stochastic gradient descent. The model is evaluated using metrics such as accuracy, precision, recall and F1 score and can be fine-tuned using techniques such as hyperparameter optimization, regularization or early stopping (case study).

Once trained, the CNN model is able to predict the likelihood of a blackout event occurring within a given time window, based on the data and features.

Residual networks represent a type of convolutional neural networks (CNN) (Cui et al., 2016), which has been designed mainly to recognize visual patterns directly from pixel images with minimal preprocessing (Wang et al., 2017). ResNet can be also used for time series datasets. Since the data delivered in a smart grid (weather readings) are a time series, the model structure is used for this matter.

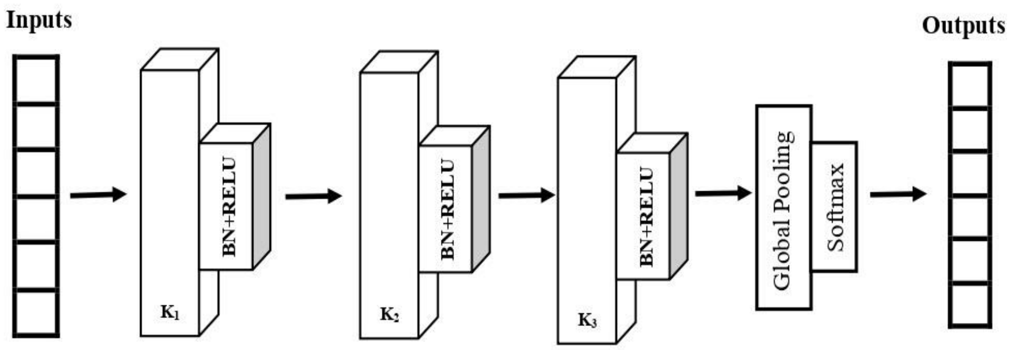

Figure 2. *Fully convolutional network (FCN) structure. Source: (Khediri et al., 2019).*

ResNet has the same structure as fully convolutional networks (Figure 2) with a deeper structure. In time series settings, the FCN is performed as a feature extractor. The softmax layer is responsible for the final outputs. A convolutional layer followed by a batch normalization layer and a rectified linear unit (ReLU) activation layer represent the basic block.

$$\begin{aligned} y &= W \otimes x + b \\ s &= BN(y) \\ h &= ReLU(s) \end{aligned} \tag{1}$$

Where ⊗ is the convolution operator. The final networks are built by piling three convolutional blocks with the filter sizes K_i {64, 128, 128}.

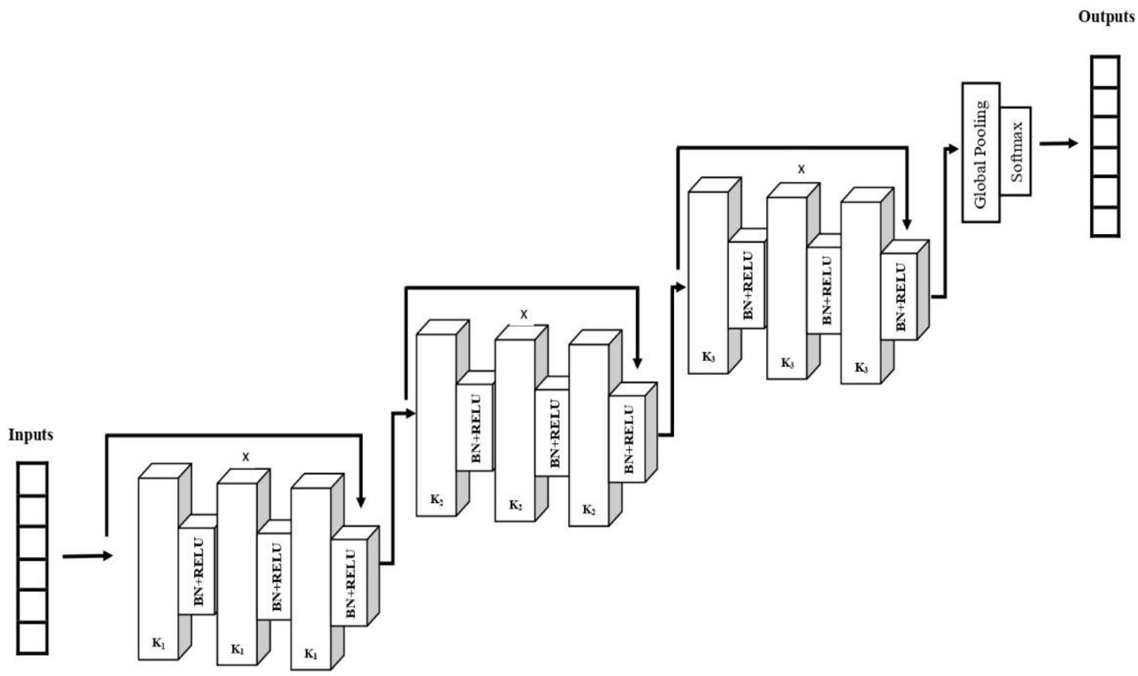

Figure 3. *Residual network (ResNet) structure.*

The neural networks are extended by the ResNet to add deep structures by adding the shortcut connection in each residual block (Figure 3). The convolutional blocks in Equation (1) are reused to build each residual block. *Block k* indicates the convolutional block with the number of filters *k*.

$$\begin{aligned} h_1 &= Block_{K1}(x) \\ h_2 &= Block_{K2}(h_1) \\ h_3 &= Block_{K3}(h_2) \end{aligned} \tag{2}$$

$$y = h_3 + x$$
$$h = ReLU(y)$$

The number of filters k_i = {64, 128, 128}. Three stacked residual blocks and followed by a global average pooling layer and a softmax layer forms the final ResNet.

Output layer: This layer applies a softmax activation function to the output of the previous layer, producing a probability distribution over the possible classes (e.g., low risk, moderate risk, high risk, extremely high risk). The class with the highest probability is the model prediction.

Algorithm 2. *CNN function pseudo-code.*

```
define CNN_model(processed_data)
define model architecture
for each time window in processed_data:
input data to model
if model output is within threshold for low blackout risk:
label time window as "low risk"
else if model output is within threshold for moderate blackout
risk:
label time window as "moderate risk"
else if model output is within threshold for high blackout risk:
label time window as "high risk"
else:
label time window as "extremely high risk"
load trained model weights
apply model to processed data
for each time window in processed_data:
if model output differs from label:
update model weights
return model output (blackout risk prediction)
```

The CNN model function takes as input a dataset of processed data, which consists of time windows of data collected from various sources related to the operation of a smart grid. The function first defines the architecture of a model, which specifies the structure and behaviour of the model. The function then iterates over each time window in the processed data, inputting the data to the model.

Based on the model output, the time window is labelled as "low risk", "moderate risk", "high risk" or "extremely high risk" depending on where the model output falls within a range of thresholds. These thresholds are determined based on the expected likelihood of a blackout event occurring.

Next, the function loads a trained version of the model, which has already been adjusted to make accurate predictions based on previously labelled data. The function then applies the trained model to the processed data and, for each time window, checks to see whether the model output differs from the label. If it does, the model weights are updated to better reflect the data and improve the model prediction accuracy. Finally, the function returns the model output, which consists of a prediction of the blackout risk for each time window in the processed data.

The CNN model function is designed to predict the risk of blackout events in smart grids. It takes in processed data as input, which is expected to be in a suitable format for model input. The function begins by defining the architecture of the model, which specifies the structure and parameters of the model.

Next, the function loops through each time window in the processed data and inputs the data into the model. The model then generates a prediction for the blackout risk of the time window. If the model prediction is within a certain threshold for low risk, the time window is labelled as "low risk". If the prediction falls within a different threshold for moderate risk, the time window is labelled as "moderate risk". If the prediction falls within a different threshold for high risk, the time window is labelled as "high risk". If the prediction falls outside these thresholds, the time window is labelled as "extremely high risk".

After the time windows have been labelled, the function loads the trained model weights, which are the learned parameters of the model that have been previously determined through training on a dataset. The function then applies the model to the processed data, using the trained model weights.

Finally, the function loops through each time window again and checks whether the model prediction differs from the label assigned to the time window. If the prediction differs from the label, the model weights are updated in an effort to improve the model accuracy. The function then returns the model output, which is the predicted blackout risk for each time window.

3.3 Alert generation

This component is responsible for generating alerts based on the predictions of the CNN model and for providing notifications for grid operators and other relevant parties. The alerts can be generated using a threshold or criteria defined by the system, such as the probability or likelihood of a blackout event occurring. For example, the system can generate an alert if the probability of a blackout event occurring within the next hour is greater than 50%.

The alerts can be generated in real time, as the data are collected and processed by the system or on a scheduled basis, such as every hour or every day. The alerts can be delivered using various communication channels, such as email, SMS or push notifications and can be customized based on the severity and likelihood of the predicted blackout event.

Algorithm 3. *Alert generation function pseudo-code.*

```
define alert_generation(blackout_risk_prediction)
define thresholds for generating alerts
if blackout_risk_prediction is above extremely high risk
threshold:
generate extremely high risk alert
  else if blackout_risk_prediction is above high risk threshold:
generate high risk alert
       else if blackout_risk_prediction is above medium risk
threshold:
generate medium risk alert
             else if blackout_risk_prediction is above low risk
threshold:
                        generate low risk alert
             end if
        end if
  end if
include information about predicted probability of blackout event
recommend monitoring the situation % being prepared for possible
preventive action
else:
do not generate alert
end if
end
```

The alerts can include information such as the predicted probability or likelihood of a blackout event occurring, the expected duration and impact of the event and recommendations for preventive or remedial action. For example, the alert can recommend reducing power demand, transferring load to other parts of the grid or activating emergency procedures.

3.4 Response management

This component is responsible for managing the response to blackout events, based on the alerts generated by the system. This can involve activating emergency procedures, deploying resources or implement preventive measures as appropriate in response to a low, medium, high or extremely high risk alert. These preventive measures could help to prevent or mitigate the impacts of blackout events. The response is triggered automatically, based on the severity and likelihood of the predicted blackout event, or initiated manually by grid operators or other relevant parties.

Algorithm 4. *Response management function pseudo-code.*

```
define response_management(alert, blackout_risk_prediction)
    if alert is generated:
        if blackout_risk_prediction is increasing:
            activate emergency shutdown procedures
        else:
            notify grid operators of potential blackout risk
            implement preventive measures as appropriate
    else:
        do nothing
```

The response can involve actions such as reducing power demand by shutting down non-critical loads, transferring load to other parts of the grid or activating emergency generation sources. The response can also involve deploying resources such as generators, transformers or other equipment to restore power or repair damage to the grid.

3.5 User interface

This component provides a user-friendly interface for grid operators to access the system and view the alerts generated by the CNN model. The interface is web-based or mobile-based and is accessed using a web browser or app. The interface can include features such as visualizations of data and predictions and options for managing the response to blackout events. The interface allows grid operators to view the current status and predictions of the system and to configure the system settings.

To integrate these four components into a complete early warning system, we can create a main function that coordinates the flow of data and calls each of the individual functions as needed.

Algorithm 5. *Main function pseudo-code.*

```
define blackout_warning_system()
    while grid is operating:
        retrieve raw data from grid sources
        processed_data = data_preprocessing(raw_data)
        blackout_risk_prediction = s_cnn_model(processed_data)
```

```
alert = alert_generation(blackout_risk_prediction)
response_management(alert, blackout_risk_prediction)
```

This main function retrieves raw data from the grid sources, processes the data using the data preprocessing function, generates a blackout risk prediction using the CNN model function, generates an alert using the alert generation function and manages the response to the alert using the response management function. The main function runs continuously while the grid is operating, allowing the early warning system to continuously monitor the grid and respond to changes in blackout risk.

4 Case study

4.1 Case description

A prototype is created utilizing the Python programming language and many deep learning and machine learning technologies, such as TensorFlow and Keras, in order to verify our proposal. Real data from Seattle City Light's historical outage reports and maintenance records are used in our study (Table 2). The collection includes 42,406 entries in total, representing various outage events. A total of 27,564 instances (65% of the total items) were used to train the model. The dataset is public (see Data Availability statement) and has been used in earlier studies (Khediri et al., 2020; Khediri et al., 2021).

4.2 Methodology

Hyperparameters were fine-tuned to optimize model performance. The learning rate was selected from a range of {0.1, ..., 0.00001} through validation error minimization and the batch size was maintained at 10 to balance computational efficiency and model convergence. No regularization techniques were employed aside from early stopping.

Utilizing a GPU-accelerated environment, training the CNN model for 120 epochs on a NVIDIA GeForce RTX 2080 GPU yielded promising results. Pre-training of the model took 60 seconds, with an average of 0.5 seconds per epoch. Fine-tuning, conducted after pre-training, was completed in 35 seconds or 0.29 seconds per epoch.

The hyperparameters were selected by optimizing on the validation error. We tested learning rates in {0.1, …, 0.00001}. There was no use of any form of regularization besides early-stopping, nor optimization over the number of pre-training updates.

Table 2. *Experiment summary.*

Total number of items (outages)	42,406
Used to train the model	27,564
Batch size	10
Learning rate	[0.1, 0.01, …, 0.00001]
Number of hidden layers	3

4.3 Results

Different deep learning algorithms are used in our experiments such as recurrent neural networks (RNN), variational autoencoders (VAE), transformers and others, in order to validate our proposal. The same dataset is used to train the models with the same number of items. Accuracy and precision are calculated for each model.

Table 3. *Final result for the experiments.*

Model	Labelled as 0 classified as 0	Labelled as 0 classified as 1	Labelled as 1 classified as 0	Labelled as 1 classified as 1	Accuracy	Precision
VAE	12,642	97	538	1,565	0.9572	0.9592
Transformers	10,982	355	870	2,635	0.9175	0.9266
RNN	9,882	862	1,135	2,963	0.8654	0.8970
ResNet	12,971	14	177	1,680	0.9871	0.9865

The final experiment results (Table 3) give us an accuracy rate of 98.71% and a precision rate of 98.65% for the ResNet model, which are the best results among all the models (Figure 4).

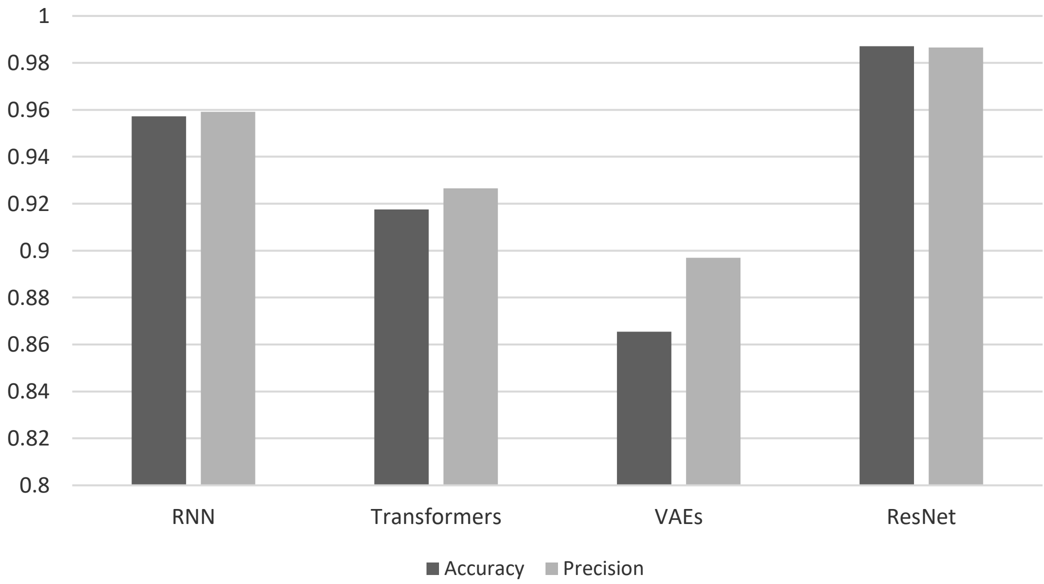

Figure 4. *Results of Accuracy and Precision presented in the graph.*

5 Discussion

From the experiments that were carried out, we can affirm that the results are quite convincing, which proves that the proposed model could be used perfectly for blackout prediction and for resilience enhancement generally. These results show that the proposed early warning system can offer quite convincing results and can be used by electricity distribution networks at all levels.

The proposed approach is based on a ResNet CNN model and the DSOM, which work together to provide highly accurate predictions of blackout events. The use of the DSOM helps learn features from the data and identify patterns and trends, which improves the performance of the CNN model. The resulting system offers predictions with a low false alarm rate and can be customized and scaled to suit the needs of different electricity distribution networks. These features of the system are crucial in ensuring that it provides significant benefits such as improved resilience, enhanced reliability, cost savings, improved safety and environmental benefits.

However, the proposed early warning system stands as a promising innovation, yet its successful implementation requires acknowledgment of certain inherent limitations. The system efficacy hinges on the responsiveness of operators to generated warnings, necessitating meticulous training strategies and protocols to ensure timely action.

The vital concern of cybersecurity requires dedicated actions to protect the system from possible attacks. Although the predictive abilities of the system are groundbreaking, it has yet to be tested for its accuracy in forecasting complex blackout events. Additionally, the current scope of prediction is limited by the use of specific datasets, suggesting potential for expansion to cover a wider range of threat scenarios. Together, these limitations highlight the intricate context in which the early warning system operates, emphasizing the need for ongoing research to strengthen its effectiveness and reliability.

6 Conclusion

In conclusion, early warning of blackout events in smart grids is a critical challenge, as these events can have significant impacts on individuals, communities and businesses. There is a need for effective approaches and technologies to predict and prevent blackout events and to enhance the resilience and reliability of grids.

The CNN deep learning algorithm and the other components described in this paper offer a promising approach to addressing this challenge, as demonstrated by the high precision (98.65%) and accuracy (98.71%) of the CNN model in predicting blackout events. The use of machine learning algorithms, data analytics, real-time monitoring, probabilistic and statistical models, control and optimization techniques and the integration of multiple technologies can provide a foundation for an early warning system that is capable of predicting blackout events in real time, with high accuracy and low false alarm rates.

Conducting further research is imperative to systematically explore potential avenues for enhancing system efficiency. This potential direction holds promise for advancing the field of efficient energy systems and contributing to its ongoing evolution.

Additional Information and Declarations

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: A.K.: Conceptualization; methodology; software; validation; formal analysis; investigation; data curation; writing – original draft; writing – review and editing; visualization; supervision; project administration. A.Y.: Conceptualization; methodology; software; validation; formal analysis; investigation; writing – review and editing; project administration. M.R.L.: Data curation; resources; investigation; supervision; writing – review and editing. Y.B.: Resources; writing – review and editing; supervision.

Data Availability: The dataset used is public and has been published by *Major Power Outage Risks in the U.S. – Laboratory for Advancing Sustainable Critical Infrastructure, Purdue University*. The dataset is accessible at: https://engineering.purdue.edu/LASCI/research-data/outages

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