Research Article

A Hybrid Convolutional Neural Network and Relief-F Algorithm for Fault Power Line Recognition in Internet of Things-Based Smart Grids

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Today, energy management based on the digitalization of smart grids by the Internet of Things (IoT) is an emerging paradigm for power line systems. There are several environmental hazards to break down high-voltage power cables such as lightning, severe voltage fluctuations, and incorrect design of electric field distribution. So, identifying faulty high-voltage power lines is one of the most emerging challenges in smart grids to avoid disruption of the power distribution networks. This paper presents a new hybrid Convolutional Neural Network and Relief-F (CNN-RF) algorithm for an energy-aware collaborative learning approach to detect power line systems in smart grids. This hybrid approach ensures the stability and reliability of the defective power line system and improves the energy efficiency of the smart grids. This approach can detect the defective power line recognition using damaged power line images concerning automatic monitoring using Unmanned Aerial Vehicle (UAV) control system and IoT communications. By applying UAV control system and IoT communications on gathering damaged power line images, human faults and environmental hazards for extra data transmission are avoided. Experimental results show that the proposed CNN-RF model represents a high accuracy rate of 92.2% for recognizing damaged power lines. Also, the precision of damaged line detection ratio is higher than other prediction methods by the rate of 92.5%. Finally, the performance of the damaged line prediction approach in the CNN-RF method has a daily minimum cost in the IoT-based smart grids.

1. Introduction

Today, by increasing information technology and computer science paradigms on Internet of Things (IoT) [1, 2], wireless communications, and 5G technologies, smart environments can apply these paradigms to improve and facilitate resource management, optimized services, and energy efficiency factors [3, 4]. Smart grid network is one of important smart environments that energy efficiency and fault tolerant methods are considering to manage optimized services using the IoT and intelligent applications [5, 6].

In smart grid network, power cables have many dynamic modules for improving industrial power management and smart environments to create and support a safe condition for power lines in electricity flow networks [7, 8]. Today,

high-voltage power cable examination is a critical manner for getting time and human side effects [9]. On the other hand, the IoT smart devices can help to control, trace, and detect power line systems by applying intelligent aspects and technical applications for avoiding damaged cables and power lines and energy failures in smart grids [10, 11].

Due to limited time, energy saving resources, and highly cost of checking damaged and faulty power lines, Unmanned Aerial Vehicle (UAV) control systems can help to gather and select existing optimal power line detection methods [12, 13]. So, smart grids with the help of IoT applications and smart devices can increase the accuracy of prediction methods with respect to the key solutions of machine learning and smart monitoring in smart grids [14–16]. On the other hand, capturing and gathering high-

resolution information is a critical task for detecting damaged power lines in grid networks. By using UAV control systems, a managed and collected procedure is established for power lines in smart grids [17–19].

To solve these problem statements correctly, this paper presents a new hybrid Convolutional Neural Network and Relief-F (CNN-RF) algorithm to analyze damaged and faulty power line systems in smart grids based on energy consumption factor. The proposed power line detection system includes three phases consist of collecting the image data from Unmanned Aerial Vehicle (UAV) control system and IoT communications, featuring selection method, including two main smart power grid environments such as urban and mountain, and predicting damaged cables to forward for empirical analysis and improvement procedures. The proposed CNN-RF algorithm is employed to show how on-time failure influences the power consumption and energy flow delay in smart grid network.

The main contributions of this technical research are shown as follows:

- (i) Proposing a hybrid Convolutional Neural Network and Relief-F (CNN-RF) algorithm to analyze both accuracy of prediction approach and finding failures and damaged cables
- (ii) Selecting optimal operators that are applied to the prediction stage using RF algorithm
- (iii) Facilitating modifiability and energy management according to predicted damaged power lines in smart power grid network

The structure of this paper is shown as follows: the literature related to the fault detection methods using artificial intelligence in the smart grid and IoT industry is reviewed in Section 2, the proposed methods for detection of damaged and crashed power lines are introduced in Section 3, the experimental results are discussed in Section 4, and the discussion and conclusions are shown in Section 5.

2. Related Work

This section discusses a brief motivation about existing case studies on fault detection methods using artificial intelligence in the smart grid and IoT industry. For example, this work [20] presented a power cable model with sets of essential points for power cable discovery. The offered design of discovery is short and precise since the endpoints and the curve equation per cable are contained in the classified essential points. Moreover, a new model based on the CNN algorithm model was presented to forecast classes of points on power cables in the visual image instantly. In this study, a new positive instance checking procedure was instructed to discover the unique idea of cable essential point's discovery by applying the pixels along each power cable as positive instances for essential points voting and forecast.

Another work [21] presented a generalized focal loss function established on the Matthews correlation coefficient

to handle the class inequality issue in PL segmentation while using a generic deep segmentation structure. The loss function was assessed by enhancing the vanilla U-Net model with an extra convolutional auxiliary classifier head for more suitable learning and quick model conjunction. The evaluation of two PL datasets demonstrated that the presented loss function outperforms the famous BBCE loss in PL dice scores on both the datasets, accuracy, and false detection rate values.

Mukherjee et al. [22] presented a relative analysis of three separate deep learning standards with a traditional machine learning standard to define the most useful multilabel classifier for the recognition of data intrusion areas has been done. Analysis results showed that the power flow correlation characteristics and locational recognition of FDIA can be proposed as a multilabel classification issue. Comprehensive assessments have been performed to specify the parameter sensitivity over the presented structure. Tian et al. [23] offered a new mixed deep learning instrument to determine the damages in the communication cables. This structure included CNN and SVM that CNN is used for the category of damaged power cables pictures, and SVM is for the recognition and estimating the intensity of damaged power cables using statistical information. The importance of this study contains no additional communication cables control and checkup fees.

Xia et al. [24] suggested a collaborative detection instrument for false data attacks. A trust-based compromised PMU recognition method was proposed to determine negative PMUs by scanning manners of PMUs in a process. Moreover, a voting-based discovery strategy was presented based on physical directions to catch FDIA collaboratively. This strategy enhanced the recognition speed while decreasing the computational charge at the control center. The empirical outcomes using the PowerWorld simulator demonstrated the efficiency and usefulness of the presented mechanism and strategies. Zhang et al. [25] designed an objective power cable discovery approach employing convolutional and modeled components. A convolutional neural network was constructed to receive hierarchical reactions from a separate layer. Moreover, the rich component maps are combined to build a fusion outcome, and the modeled information consists of length, width, orientation, and the area received from the most unsophisticated component map. Eventually, the fusion outcome is combined with modeled information to reach an outcome with obvious experience.

According to the above-related works, there are some limitations to enhancing the prediction of damaged power lines and cables in smart grids. With respect to the above limitations, the next section presents a new hybrid model to predict damaged and faulty points of power lines using the information of UAV control systems in IoT-enabled power grids.

3. Proposed Method

Detection of damaged and crashed power lines is an important way to check and modify various faults in smart grids. It

FIGURE 1: Applied correlation method on an image sample of power lines in the urban dataset.

FIGURE 2: Image sample example with applied correlation method in the power lines mountain dataset.

is particularly suitable for evaluating urban and mountain power lines with respect to the UAV data collections. Our ideal to detect edge-based UAV pictures is based on a smart model that UAV control systems collect all images and map according to existing variables including L as a set of m rows and m columns of pixels. We define A as the number of edge lines, and M is a set of colors in the edge lines that show $(m_1, m_2, m_3 \dots m_k)$ a real-time safety critical system [26].

According to power line detection, we present a new hybrid Convolutional Neural Network and Relief-F (CNN-RF) algorithm that we used CNN algorithm based on the classification and recognition procedures in [20, 27, 28].

The proposed CNN algorithm has a set of 4-tuple structure $N = (E, D, O, C)$ variables that are mainly reflected to cluster image parameters of the existing samples where [29, 30]

- (i) E is an encoding platform with 7 layers to cluster scattered important points of power lines
- (ii) D is a decoder for classifying key points of power lines from UAV images directly to the detailed pixels of damaged cables
- (iii) O is a set of operators that are applied to the prediction stage with three functional subnets to train procedures in power line detection
- (iv) C is a final clustering function to show damaged and faulty positions of power lines and cables in smart grid images

For optimizing the matching method for existing pixels along power lines as applied samples and train existing pixels with sets of m rows and m columns as encoded vectors, we apply the Relief-F algorithm [31]. The Relief-F algorithm was defined and applied to many research topics [32]. The algorithm is applied for classifying continuous values in images. The Relief-F algorithm mainly includes three main levels: intratrain distribution, intertrain distribution, and update features. In this procedure, the Relief-F algorithm can extend a random sample R as a targeted image from the set of training samples. After choosing a random sample, this algorithm selects a set of neighbors as R number of samples to update the weight of each pixel value as a targeted feature according to Equation (1) [33, 34].

$$F(A) = F(A) - \sum_j^k \Delta(L, R, H_j) + \sum_{\text{class}(R)}^n \frac{P(K)}{1 - p(\text{class}(R))}. \quad (1)$$

According to Equation (1), function $F(A)$ is defined as updated feature selection and previous features where $\Delta(L, R, H_j)$ represents the difference between sample R_i as new feature selection and sample R_j as previous features on the characteristic L , and as shown in Equation (2), H_j represents the j nearest neighbor sample in class K [35]. Final value of the H is categorized into three types

FIGURE 3: Accuracy evaluation on cross-folds 5, 10, 15, and 20 in the PLDU dataset.

FIGURE 4: Accuracy evaluation on cross-folds 5, 10, 15, and 20 in the PLDM dataset.

including a continuous value, 0, and 1 according to Equation (1) [34].

$$\Delta(L, R, H_j) = H, \quad (2)$$

$$H = \begin{cases} \frac{|R_i[L] - R_j[L]|}{\max(L) - \min(L)}, & \text{if } L \text{ is a continuous value,} \\ 0 & R_i[L] = R_j[L], \\ 1 & R_i[L] \neq R_j[L]. \end{cases} \quad (3)$$

For enhancing the effectiveness of the proposed hybrid CNN-RF algorithm, we calibrate the assigned classes to each set of targeted pixels in the sample power line images. In real images, there exist millions of different

pixels, and we can calibrate targeted pixels with an approximate evaluation to divide the entire sample area into $k \times m$ detection regions C_{km} . The size of each image C_i was defined as follows [36]:

$$C_i = (\text{width} = 100\text{pix} \approx 100\text{m}, \text{height} 100\text{pix} \approx 100\text{m}). \quad (4)$$

According to the above technical aspects, the proposed CNN-RF algorithm can perfectly select important key features based on targeted pixels in the UAV images.

4. Experimental Results

In this section, a series of experimental results are evaluated to validate the proposed method's efficiency. For analyzing the proposed CNN-RF prediction model, we

FIGURE 5: Precision-recall curves on the PLDU dataset.

FIGURE 6: Precision-recall curves on the PLDM dataset.

used two popular power line detection datasets (<https://github.com/SnorkerHeng/PLD-UAV>) with high-pixel observations in urban locations (Power Line Detection in Urban (PLDU)) and mountain-desert locations (Power Line Detection in Mountain (PLDM)) as shown in Figures 1 and 2. To capture the damaged and disrupted power line images in the PLDU and PLDM datasets, UAV control systems have flown above the power line locations within ten and thirty meters, respectively. For achieving optimal prediction results, we categorized 453 samples of images for training and 120 samples for testing methods in the PLDU dataset. Also, from 287 total samples of images in the PLDM dataset, we divided 237 samples for training and 50 samples for testing methods. The experimental results are performed on NVIDIA 4-

Plus-1 ARM Cortex-A15 CPU, 192 CUDA core, and 16 DDR4 memory in MATLAB R2021a.

According to the prediction evaluation, the proposed CNN-RF method is compared to some newly released mechanisms to detect damaged power lines with UAV and the IoT technologies including Convolutional Neural Network (CNN) [20], CNN [37] and Support Vector Machine (CNN-SVM) [23], Focal Phi Loss (FPL) [21, 38], and convolutional features and structured constraints (CFSC) [25, 39].

Our research is based on the results of feature selection and finally completes the diagnosis of breast masses through the classifier. To evaluate and compare the performance of feature selection techniques using the two-stage feature selection method and other algorithms, three performance

measures, namely, accuracy, precision, and recall, are shown in Equation (5).

$$\begin{aligned} \text{Accuracy} &= \frac{\text{true positive} + \text{true negative}}{\text{true positive} + \text{true negative} + \text{false positive} + \text{false negative}}, \\ \text{Precision} &= \frac{\text{true positive}}{\text{true positive} + \text{false positive}}, \\ \text{Recall} &= \frac{\text{true positive}}{\text{true positive} + \text{false negative}}. \end{aligned} \quad (5)$$

Figure 3 shows the comparison of accuracy factors for existing prediction models in the PLDU dataset. The red line in the figure indicates the estimated latency equals the ground truth. That is, the prediction model accurately estimates the actual latency. The blue line shows the accuracy of the CNN-RF method to detect damaged power line images in cross-folds 5, 10, 15, and 20 that have better estimation performance of the prediction model than other methods. It can be seen that as compared with benchmarking prediction models, our prediction model can estimate the damaged power lines in urban images more accurately.

Figure 4 illustrates the accuracy evaluation with recent works and the proposed CNN-RF method in the PLDM dataset, where our method realizes substantially better performance than CNN, CNN-SVM, FPL, and CFSC.

Figure 5 suggests the percentage of precision-recall curves using different machine learning algorithms and the number of cross-folds, respectively. The proposed CNN-RF method has the highest ratio than other CNN, CNN-SVM, FPL, and CFSC algorithms to detect damaged power lines in urban environments. Also, Figure 6 depicts the percentage of precision-recall curves using different machine learning algorithms and the number of cross-folds for PLDM dataset, respectively. The proposed CNN-RF method has the highest ratio than other algorithms to select damaged power lines in environments.

5. Conclusion

This paper presented a hybrid CNN-RF method for IoT-enabled fault power line detection to find the optimum prediction performance among crashed and damaged power cables and lines. Two important different datasets, namely, PLDM and PLDU concerning UAV control systems, were compared. This comparison has shown rather varying behaviors of the two datasets to support the optimum prediction performance. The experimental results show that the proposed CNN-RF method has a maximum accuracy ratio for predicting damaged power lines up to 97% for power line recognition in urban environments. Also, we observed that the proposed CNN-RF method illustrated optimum accuracy performance for detecting damaged cables in the mountain and out of cities with 92% better than other recent case studies including CNN, CNN-SVM, FPL, and CFSC. Finally, the proposed CNN-RF method has a better precision-recall ratio than other algorithms. However, our proposed method has

some limitations. First, we approximate the proposed model just to check power lines in a static environment after gathering the UAV control system as offline mode. Second, we discovered some problems of urban power lines that technical secretaries have modified damaged power lines in an on-time schedule. So, there are some gaps between damaged images and real fixed cables in urban environments. In future works, some other powerful metaheuristic algorithms can be applied to find optimal feature selection method and increasing accuracy of damaged fault prediction in power lines.

Data Availability

The experiment data supporting this experiment evaluation are from the following reported studies, which were cited and are included within the articles: Jaffari et al. [21]: A Novel Focal Phi Loss for Power Line Segmentation with Auxiliary Classifier U-Net (Sensors, 21(8), 2803) and Dai et al. [20]: Fast and Accurate Cable Detection Using CNN (Applied Intelligence, 50(12), 4688-4707).

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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