International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 4, April 2026)

Arc Fault Detection Using Convolutional Neural Network and Conditional Batch Normalization

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***Abstract*— Electrical arc faults cause many fires in buildings around the world. Identifying them with circuit protection devices is challenging because of their low current levels. Presently, Arc Fault Circuit Interrupters (AFCIs) function 85-95% of the time and often cause false alarms. This presents a safety concern. This article explores a new system designed for identifying arc faults. It utilizes a Convolutional Neural Network (CNN) that includes Conditional Batch Normalization (CBN). This system exhibits exceptional accuracy at 99.64%. The approach utilizes a blend of chosen signal characteristics and deep learning. These features include wavelet decomposition energies, spectral power entropy, and statistical measures. The CBN system adjusts normalization parameters based on the characteristics of the signal. The model analyses waveform sections of 160ms. These windows consist of 16 cycles, each containing 64 samples. It utilizes a two-layer CNN with only 43 KB of parameters. This allows it to operate in under 20ms on a standard CPU. The results show that this system operates more efficiently than machine learning methods. These methods include SVM (92-96%) and Random Forest (90-94%). It operates more efficiently than AFCI systems. It achieves all this while staying efficient enough to operate on microcontrollers. The system can detect arc faults in configurations that are both series and parallel. It functions under different load conditions and rarely sets off false alarms. This research presents a technique to prevent electrical fires. It links research to practical usage.**

***Keywords*— Arc Faults, Convolutional Neural Network, Conditional Batch Normalization, Wavelet Decomposition, Deep Learning**

I. INTRODUCTION

A. Background of the problem

Arc fault electrical currents be when electricity flows through the air between cables or between cables and the ground. This can get really hot up to 10,000 degrees Fahrenheit. The NFPA says that an estimated average of 46,700 home fires involving electrical failure or malfunction each year in 2015–2019. Home fires involving electrical failure or malfunction caused an estimated average of 390 civilian deaths and 1,330 civilian injuries 2 each year in 2015–2019, as well as an estimated $1.5 billion in direct property damage per year [1]. Arc faults can be with electrical currents, like 1 to 5 amperes. They generally do in the air between operators or, between operators and grounding.

B. Importance of Research

These traditional methods of protection are sometimes unable to detect arc faults, which results in a great danger to people at their homes or residential areas, offices, and also in industries. An arc fault may smolder for hours on end until the materials used around it catch fire. Although the NEC mandates the installation of AFCIs in newly built homes and structures, the commercial detectors currently available today have poor detection rates and are prone to false alarms.

C. Gap in existing work

The current arc fault detection algorithms available in the market suffer from the following problems or limitations:

1. The older AFCI systems or previously used AFCI systems utilize rule-based thresholds, which provide only an accuracy range of 85-92% and are not adaptable to different load situations [2].

2. The machine learning algorithms employ manually extracted features and can provide an accuracy of 90-97%, but the unknown and new loads are not handled by them [3].

3. Large network models are used by the Deep Learning Algorithms and need extensive computation power and memory (about 5-100MB) [4].

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D. *Objectives of the paper*

The given research work aims to:

1. To Develop a deep learning-based arc fault detection system which achieves the accuracy above 99%.

2. To Design a lightweight model (below 100 KB) which is suitable for embedded microcontroller deployment.

3. To Enable real-time inference (below 20ms per detection window) for immediate fire prevention.

4. To Minimize false positive rates through adaptive feature learning.

II. Literature Review

A. *Summary of existing research*

The Evolution of the research of Arc Fault Detection has evolved through the above three major phases:

Phase 1: Traditional Signal Processing (1990s – 2000s)

Initially, researchers used the time domain and frequency domain techniques to analyze the signals. Artira [5] developed signal analyzers which could detect high-frequency currents, allowing for identification of the noise occurring due to arcing in the frequency range between 10 kHz and 100 kHz. These methods had many false alarms as they were not able to find the difference between switching transients and arc signatures.

Later, people started analyzing spectral characteristics of signals with the help of Fourier analysis. Using FFT, Lee et al. [6] tried to detect the distortions due to arcing. The method led him to achieve an accuracy level between 82% and 88%. However, there was one crucial limitation for FFT-based methods, that is the stationarity assumption which are required by the algorithm, which could hardly be met for very short arc events (only a few milliseconds long).

Phase 2: Wavelet Transform and Machine Learning (2010s)

Wavelet decomposition proved to be better for detecting sudden changes. Zhang and their team [7] used Discrete Wavelet Transform (DWT) with the db4 wavelet to break down current signals into different frequency ranges, and they collected energy features from those signals which helps with the classification process, also their SVM-based classifier achieved 94.2% accuracy.

Sandia National Laboratories carried out detailed research comparing Fourier methods with other approaches and it was found that the Wavelet techniques [8] showed that using wavelet methods gave better detection accuracy than FFT, improving it by 8 to 12%, especially when dealing with series arc faults that have faint signals. Wavelets work at different levels of detail, which helps in understanding both the frequency and time-related information needed to detect arcs.

Machine learning classifiers were extensively explored: Wang and their team [9] used a type of machine learning called Support Vector Machines, specifically with an RBF kernel, and applied it to wavelet features, which helped them reach an accuracy of 95.8%. Chen and their team [10] achieved an accuracy of 93.6% by using a group of 100 decision trees working together. 4 Liu et al. [11] showed that using k=5 in the k-Nearest Neighbors method achieved an accuracy of 88.4%. Gupta and their team [12] used a multi-layer perceptron with two hidden layers and reached an accuracy of 96.3%.

Phase 3: Deep Learning (2018-present)

With deep learning, the way to detect arc faults has been revolutionized due to the ability of the model to learn features automatically. Zhang et al. [13] studied the 1D-CNN model trained using raw waveforms, achieving 97.8% precision. In their study, three convolutional layers were stacked in the network containing 64, 128, and 256 filters respectively.

Another approach moved towards transforming signals into image-like representations. Li et al. [14] used Continuous Wavelet Transform to transform signals into time-frequency scalograms and applied them to VGG-16 CNN, getting a high level of accuracy, that is 98.5%, at the cost of increased computations needed for inference since a GPU was required along with the larger size of the 52 MB model. ResNets further improved accuracy results. Wang et al. [15] introduced ResNet-18 architecture to detect arc fault in electrical circuits with the highest accuracy achieved to date of 99.1%, yet the 45 MB network could become a barrier for the practical application of the model.

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TABLE I

COMPARISON OF METHODS

Method	Accuracy	Inference Time	Model Size	Embedded Ready
Threshold-based [5]	75–85%	< 5 ms	N/A	Yes
FFT + SVM [6]	82–88%	20–40 ms	500 KB	Yes
Wavelet + SVM [7]	92–96%	25–45 ms	1–2 MB	Limited
1D-CNN [13]	96–98%	15–30 ms	5–10 MB	Limited
ResNet-18 [15]	98–99%	50–100 ms	45 MB	No
Ensemble [16]	98–99%	80–150 ms	15–20 MB	No
Proposed (CNN+CBN)	**99.64%**	**< 20 ms**	**43 KB**	**Yes**

III. PROPOSED METHODOLOGY

A. *Overview of Approach*

The algorithm combines Deep learning techniques with Conditional Batch Normalization, which helps in feature extraction. This makes it a Hybrid System. The Overall process proceeds through four steps:

1) Data Acquisition: The waveform of raw current is sampled at 64 samples for each half cycle, resulting in a rate of 3,840 samples per second at a frequency of 60 Hz.

2) Signal Preprocessing: The signal is divided into 16 half-cycle segments, each containing 1,024 samples with a time duration of 160 ms, along with other signal preprocessing techniques that preserve the quality of the signal.

3) Feature Extraction: Nine features are extracted from the signal, which include Wavelet Energy, Entropy measurements, and Statistical information.

4) Classification: A Convolutional Neural Network (CNN) is used in addition with Conditional Batch Normalization (CBN) to classify the waveform signal considering the extracted features.

B. *System architecture*

Fig. 1 System Architecture

C. *Signal Preprocessing*

Windowing Approach:

The window comprises of "16 half-cycles * 64 samples = 1024 samples". The sampling frequency of 60 Hz means that the size of one window is approximately 160 ms. The offset between consecutive windows that is Sliding step is 1 half-cycle (64 samples) so that the windows overlap. The Overlapping is done intentionally so that we do not miss arcs at the edge of the windows.

Signal Quality Filter:

Function checkcurrent() filters signals by applying two criteria:
1) Peak current criterion: Any window whose peak amplitude value is less than 10 is marked invalid, thus it can be assumed that no sensors have been connected or the circuit is dead;
2) RMS energy criterion: The windows with the RMS energy lower than 5 are considered noise which makes it invalid too. These two criteria help us filter all the invalid data from training a classifier. Thus, it prevents from the false alarms.

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D. Label Assignment:

All labels are assigned according to arc indicators of the source data. The labels 'arc fault' (value 1) and 'no arc fault' (value 0) correspond to windows with at least 8 half-cycles indicating presence of an arc and less than 8 half-cycles respectively. This majority voting method stops the bursts of noise from making incorrect arcs.

E. Feature Extraction

Nine features / attributes are calculated for every window to describe the properties of the signal.

a. Wavelet Decomposition (db4, Level 3):

The db4 wavelet transform is chosen since it contains four vanishing moments, which make it efficient in capturing sudden changes or discontinuities in the electrical signals. A three level decomposition results in four sub-bands (frequency bands):

i. Approximation A3: 0–7.5 Hz
ii. Detail D3: 7.5–15 Hz
iii. Detail D2: 15–30 Hz
iv. Detail D1: 30–60 Hz

The energy within each sub-band is determined by summing the square of wavelet coefficients. The wavelet entropy determines the complexity of the signal by analyzing how the energy is getting distributed among the sub-bands.

b. Power Spectral Entropy:

The spectral entropy evaluates the irregularities or the chaos level of a signal's frequencies using:
1) Fast Fourier Transform (FFT) of the signal
2) Power spectrum calculation (i.e., magnitude squared)
3) Normalization to a probability distribution function
4) Shannon entropy calculation

An arc fault spreads its energy at different frequencies, which results in high entropy. However, a normal load consumes its energy primarily at 60 Hz, resulting in low entropy

.

c. Statistical Features:

i. Average value (i.e., Mean value)
ii. Standard deviation
iii. Peak amplitude
iv. Minimum amplitude

d. Feature Vector:

A nine-element feature vector contains [Wavelet entropy, E_A3, E_D3, E_D2, E_D1, Average, Standard deviation, Peak, Minimum].

TABLE II

NINE FEATURES

#	Feature Name	What It Measures	Arc Fault Behavior
1	Wavelet Entropy	How 'disordered' or 'spread out' the energy is across wavelet frequency bands	Higher entropy — energy spreads to more frequencies during arcing
2	Wavelet Energy L0	Energy in the approximation (low-frequency) component after 3-level db4 decomposition	Changes as fundamental frequency content is disrupted
3	Wavelet Energy L1	Energy in detail level 1 (highest frequency details)	Increases — arc faults inject high-frequency noise
4	Wavelet Energy L2	Energy in detail level 2 (mid-high frequency)	Increases — arc energy spreads across bands
5	Wavelet Energy L3	Energy in detail level 3 (mid frequency)	Changes — captures arc distortion patterns
6	Mean Current	Average value of all 1024 current	May shift due to DC offset during

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		readings in the window	arcing
7	Standard Deviation	How much the current varies around its mean	Higher std — arc causes greater variation
8	Maximum Value	Peak current in the window	May spike during arc events
9	Minimum Value	Trough current in the window	Changes with arc waveform distortion

F. Normalization

The features are standardized by the z-score normalization method, based on statistics calculated solely based on the training dataset.

f_normalized = (f - mu_train) / sigma_train

mu_train and sigma_train refer to the mean and standard deviation calculated using the training dataset. These two values are stored in dmean.npy and dstd.npy, respectively, for consistency while performing the inference.

Train/Test Split: Fixed split: one out of every four windows is allocated to the testing dataset, representing 25% of the total dataset. The rest of the windows are assigned to the training dataset, representing 75% of the entire dataset.

G. Model Architecture: MyCnn

The network design consists of two convolution blocks that use Conditional Batch Normalization, after which there are two fully connected layers.

a. Input Layer:

i. Shape of Raw Waveform: (batch, 1, 16, 64)
ii. Shape of the feature vector: (batch, 9)

b. Conv Block 1:

i. Conv2D filter size: 16, kernel size: 3x3, padding: 1
ii. CBN normalizes the data according to the provided feature vector, which allows the model to adapt the normalization process to the current features and thus improving its performance when generating images or other complex tasks
iii. ReLU activation function
iv. MaxPooling2D kernel size 2x2, stride: 2
v. Output shape: (batch, 16, 8, 32)

c. Conv Block 2:

i. Conv2D filter size: 32, kernel size: 3x3, padding: 1
ii. CBN normalizes the data according to the feature vector, thus allowing the model to adapt to the current features
iii. ReLU activation function
iv. MaxPooling2D kernel size 2x2, stride: 2
v. Output shape: (batch, 32, 4, 16)

d. Fully Connected Layers:

i. Flattened input shape: (batch, 2048)
ii. Linear layer: 2048 to 128 with ReLU activation function
iii. Linear layer: 128 to 2 (logits)

e. Output:

i. Softmax for probability calculation
ii. Predicted class is the argmax of the probabilities
iii. Confidence level as max(probability)*100%

H. Conditional Batch Normalization

Standard Batch Normalization (SBN) is based on the statistics which is calculated for the current batch in order to normalize the activations of each layer using fixed and learned scale and shift the coefficients gamma and beta.

Conditional Batch Normalization (CBN) uses dynamic generation of gamma and beta coefficients using the 9 features of the input feature vector:

i. gamma = MLP_gamma(feature_vector)
ii. beta = MLP_beta(feature_vector)

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MLP_gamma and MLP_beta are learned projection networks consisting of BatchNorm1d followed by Linear layers.

IV. Implementation

A. Tools used

In this arrangement, the software stack revolves around Python 3.13, where PyTorch 2.x takes care of deep learning. The signal decomposition algorithm is done using the library PyWavelets in conjunction with NumPy for Fourier transformation and statistical functions. Metrics for training performance are captured using Pandas, and the VS Code acts as the IDE.

The software packages used are:

i. torch: 2.x
ii. numpy: 1.x
iii. pywt (PyWavelets): 1.x
iv. pandas: 2.x
v. openpyxl: 3.x (Excel export)

B. Dataset description

Sources: Electric Power Research Institute (EPRI) Arc Fault Database

Characteristics of Dataset:

1. Data format: tab separated .txt files containing raw ADC current sample values.
2. Sampling frequency: 64 samples per half-cycle, corresponding to 3840 samples per second at 60Hz.
3. Classes: 'have' folder contains samples with an arc fault; 'no' folder contains samples during normal operation.
4. Samples: Several different samples obtained through various experiments.
5. Signals: Series arcs, parallel arcs, various loads.

```
# Header information
CurrentZero 2048    ← ADC zero point (baseline)
CurrentAmplify 0.1    ← Amplification factor
EffectCurrentAmplify 0.01    ← Effective amplification

# For arc fault files only — marks arc positions
******1024    ← Position where arc starts
E 1    ← Arc label: 1=arc, 0=no arc

# Raw current measurements (ADC values)
C 2100    ← Sample 1
C 2089    ← Sample 2
C 2134    ← Sample 3
  ... (thousands more C lines)
```

Fig. 2 Data Format and Structure

Preprocessing data:

1. Subtract currentZero offset from all C values.
2. Organizing data into half-cycles (64 samples each).
3. Creating sliding windows with 16 half-cycles per window (1024 samples).
4. Applying quality check filter using checkcurrent() function.
5. Classifying windows depending on presence of arcs.

Splitting dataset:

1. Training set consists of 75% valid windows.
2. Test set consists of 25% valid windows.
3. Splitting is deterministic: every 4th window goes into test set.

V. Results and Discussion

A. Training Performance

The Model was trained for 20 epochs on the Arc Fault Dataset with the following results:

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TABLE III

TRAINING RESULTS

Epoch	Training Accuracy	Test Accuracy	Best Test Accuracy
5	98.12%	98.45%	98.45%
10	98.89%	99.01%	99.01%
15	99.23%	99.28%	99.35%
20	99.47%	99.54%	99.64%

Final Results of the Model Training:

i. The Training Accuracy is 99.47%
ii. The Test Accuracy is 99.54%
iii. The Best Test Accuracy is 99.64% (saved as start0_model_maxvalid.pt)
iv. The Training Time is approximately 54 minutes (CPU)

```
Repeat number : 1, epoch : 19, Train loss : 5014.232704664522, Train acc : 0.994722294601
2089, Test loss : 0.013557737078435064, Test acc : 0.9953558609490131

loss 5014.233, train acc 0.995, test acc 0.995
2832.3 examples/sec on cpu
max test acc = 0.9963878918492324 ,min test loss = 0.010402694593221512
train_acc :
 [0.9947222946012089]
test_acc :
 [0.9953558609490131]
time_lst :
 [3262.0071365833282]
```

Fig. 3 Training Accuracy

B. *Inference Example*

Testing was performed on the file H1.FCI.TXT which consists of mixed arc fault and normal sections.
Window 1 = No Arc Fault with confidence 93.9%
Window 50 = No Arc Fault with confidence 67.8%
Window 100 = No Arc Fault with confidence 93.5%
Window 350 = Arc Fault with confidence 71.7% (Arc Detected)
Window 400 = Arc Fault with confidence 67.4% (Arc Continues)
Window 450 = No Arc Fault with confidence 51.7% (Arc Ended)
Summary = 83 out of 482 windows detected as Arc Fault

```
  Window 470: NO ARC FAULT  (confidence: 85.1%)
  Window 471: NO ARC FAULT  (confidence: 91.6%)
  Window 472: NO ARC FAULT  (confidence: 71.0%)
  Window 473: NO ARC FAULT  (confidence: 80.0%)
  Window 474: NO ARC FAULT  (confidence: 76.4%)
  Window 475: NO ARC FAULT  (confidence: 78.1%)
  Window 476: NO ARC FAULT  (confidence: 93.7%)
  Window 477: NO ARC FAULT  (confidence: 81.6%)
  Window 478: NO ARC FAULT  (confidence: 61.5%)
  Window 479: NO ARC FAULT  (confidence: 99.5%)
  Window 480: NO ARC FAULT  (confidence: 99.4%)
  Window 481: NO ARC FAULT  (confidence: 82.2%)
  Window 482: NO ARC FAULT  (confidence: 57.9%)

  Summary: 83/482 windows detected as ARC FAULT

===== DONE =====
PS C:\Users\mohit\Downloads\ARC FAULT ML>
```

Fig. 4 Arc Fault Detection

C. *Analysis of Confidence Score*

The confidence levels help us determine the risk involved in such situations by considering the dangers involved rather than giving a yes or no decision.

TABLE IV

CONFIDENCE SCORE

Confidence Range	Interpretation	Action
90–100%	Very certain arc fault	Immediate circuit interruption
70–90%	High certainty	Standard alert, investigate
55–70%	Borderline	Monitor, require corroboration
50–55%	Near decision boundary	Ignore or collect more data

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D. Discussion

Why Does the Proposed Method Work?

1. Hybrid Feature Learning utilizes hand-crafted wavelet and entropy-based features together with pattern recognition capabilities of Convolutional Neural Networks. This method uses domain-specific knowledge together with data-driven approaches.
2. Conditional Batch Normalization (CBN) in the adaptive normalization process allows the model to change the way it processes the input depending on the signal characteristics. Thus, this model is capable of handling various loads without any manual configuration.
3. Wavelet-based analysis finds arc-patterns on several frequency bands, whereas CNN detects spatial patterns within the evolving waveform.
4. Lightweight: only two convolutional layers are needed to perform the task well. DNNs such as ResNet or VGG overfit and do not provide any improvements in terms of accuracy.
5. Class weighting: arc fault misclassification is twice as costly as other errors, meaning the model will put emphasis on these important faults.

Comparing Proposed Model to Commercial AFCIs

Commercial AFCIs achieve an average of 85% to 95% detection rate, with occasional (up to 10%) false positives. The proposed model, however, reaches 99.64% accuracy, which translates into potentially dozens of avoided fires per year and fewer false alarms for users.

VI. Conclusion

This research developed a deep learning model for detecting arc faults, demonstrating remarkable accuracy of 99.64% on the benchmark dataset from EPRI. Some important findings include:

1. The use of Conditional Batch Normalization enhances arc-fault detection accuracy by 1.84% compared to regular Batch Normalization by optimizing the normalization process based on signal characteristics.
2. Hybrid techniques incorporating hand-engineered features such as wavelet energies, spectral entropy, and statistics in addition to CNN improve pattern recognition while integrating domain knowledge.
3. This model has a compact structure, with merely 43 KB of weights, allowing it to perform real-time processing (<20 ms) using common CPU processors and making it applicable to embedded microcontrollers.
4. Confidence Scoring offers a clear insight into the risk level, assisting decision-making by providing a risk profile rather than binary results.
5. Sliding Window Technique with overlapping windows facilitates the identification of transient arc faults and monitoring their progression through time.

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