Hybrid CNN–LSTM Architecture for High-Accuracy Fault Detection and Anomaly Identification in Renewable-Rich Distribution Networks

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Abstract — The increasing penetration of renewable energy sources and inverter-based distributed generators has significantly altered the transient characteristics of distribution networks, leading to weaker fault currents, increased harmonic distortion, and more complex disturbance signatures. Traditional protection and monitoring schemes fail to provide adequate sensitivity under these operating conditions. This paper presents a deep-learning-based hybrid CNN–LSTM architecture designed for high-accuracy fault detection, classification, and anomaly identification in modern distribution grids. The CNN component extracts discriminative spatial features from fault-induced spectrograms, while the LSTM layer captures temporal evolution in waveform patterns. The proposed architecture was trained on 4,800 simulated transient events and validated using high-frequency (20 kHz) waveform data generated from an IEEE 33-bus distribution system with 30% PV penetration. The hybrid CNN–LSTM classifier achieved a testing accuracy of 98.12%, outperforming standalone CNN, LSTM, SVM, and wavelet-based classifiers. The Autoencoder achieved an AUC of 0.98 for anomaly detection. The results demonstrate that the proposed hybrid architecture provides robust performance under noise, high-impedance fault conditions, and renewable-induced distortions, offering a strong foundation for next-generation adaptive protection and monitoring systems.

Keywords: Hybrid Deep Learning, CNN–LSTM, Fault Classification, Anomaly Detection, High-Impedance Faults, Renewable Energy, Distribution Networks, Autoencoder, Smart Grid Protection

I. INTRODUCTION

Modern distribution networks are undergoing rapid transformation due to the increasing integration of inverter-based renewable energy sources, electric vehicle charging stations, and advanced power electronic converters. While these developments improve sustainability and operational flexibility, they simultaneously introduce significant challenges in grid protection, fault monitoring, and anomaly detection. High penetration of photovoltaic (PV) units reduces system inertia and alters fault current magnitudes, often resulting in weak or distorted transient signatures. Such characteristics degrade the performance of conventional overcurrent relays, impedance-based fault detectors, and rule-based protection schemes that rely on predictable fault waveforms. Consequently, there is a pressing need for intelligent algorithms capable of extracting complex feature patterns, recognizing non-linear disturbances, and adapting to evolving grid conditions.

Traditional fault detection approaches—such as Discrete Wavelet Transform (DWT), Hilbert–Huang Transform (HHT), and statistical signal-processing techniques—have achieved reasonable success under ideal conditions. However, their reliance on handcrafted features limits their robustness when transient signatures are weak, masked by noise, or highly variable due to distributed energy resources. Similarly, classical machine learning classifiers such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (kNN) struggle with high-dimensional waveform data and poorly capture temporal dependencies inherent in transient events.

Deep learning has emerged as a powerful solution for analyzing complex power system measurements. Convolutional Neural Networks (CNNs) are widely recognized for their ability to extract hierarchical spatial features from time–frequency representations such as spectrograms, enabling them to capture harmonic distortions, abrupt changes, and fault-induced energy clusters. On the other hand, Long Short-Term Memory (LSTM) networks specialize in modeling temporal evolution, making them suitable for identifying sequential waveform dynamics. Combining both architectures in a hybrid CNN–LSTM model provides a complementary learning mechanism that captures both spatial and temporal characteristics of electrical transients, resulting in enhanced classification accuracy and robustness.

In addition to fault classification, modern smart grids require the ability to detect subtle anomalies that do not correspond to classical fault categories but may indicate early-stage equipment failures or power quality degradation. Examples include harmonic pollution caused by inverter nonlinearity, sensor calibration drift, voltage sags from cloud movement over PV systems, and frequency deviations during rapid load variations. These anomalies often lack clear labels and are challenging to detect using supervised learning approaches. Autoencoders, through unsupervised reconstruction learning, offer an effective solution by learning the normal operational behavior and identifying deviations that exhibit high reconstruction errors.

This paper proposes a comprehensive hybrid deep-learning architecture incorporating a CNN–LSTM fault classifier and an Autoencoder-based anomaly detector tailored for renewable-rich distribution networks. The proposed model is validated using high-frequency transient data generated from a detailed simulation of the IEEE 33-bus system with 30% solar PV penetration. The results demonstrate significant improvements in accuracy, detection speed, and robustness compared to conventional methods. This work contributes toward the development of adaptive, data-driven protection schemes capable of addressing the emerging challenges of next-generation smart grids.

II. RELATED WORK

The evolution of intelligent protection and monitoring systems for distribution networks has driven extensive research in the areas of fault detection, waveform classification, and anomaly identification. This section reviews key contributions in each domain and identifies the gaps that motivate the development of the proposed hybrid CNN–LSTM architecture.

A. Classical Fault Detection and Signal Processing Methods

Historically, distribution system fault detection relied on techniques such as overcurrent relays, impedance-based distance protection, and differential relaying. These schemes remain effective for strong, well-defined faults but often fail when applied to modern networks with high levels of inverter-based distributed generation (IBDG). Renewable penetration reduces short-circuit current contributions, resulting in low-magnitude, distorted fault signatures. Moreover, adaptive relays and recloser coordination become increasingly difficult due to bidirectional power flows and time-varying fault currents.

Signal-processing-based methods, including Discrete Wavelet Transform (DWT), S-transform, and Hilbert–Huang Transform (HHT), have been widely applied for transient analysis in distribution networks. Although effective in extracting high-frequency components, these methods rely heavily on handcrafted feature selection, limiting their performance under noise and non-linear distortions. They also struggle to capture long-term temporal dependencies inherent in sequential waveform evolution.

B. Machine Learning Approaches for Fault and Disturbance Classification

Machine learning techniques such as Support Vector Machines (SVM), K-nearest Neighbors (kNN), and Random Forests (RF) have been employed for waveform-based fault classification. While these approaches improve upon traditional rule-based techniques, they require pre-engineered feature sets derived from Fourier or wavelet analysis. Their performance deteriorates when subjected to:

- high-impedance fault (HIF) conditions
- harmonically rich signals from PV inverters
- measurement noise
- weak and delayed transients

Additionally, ML models cannot inherently learn spatial–temporal patterns from raw waveform data, limiting scalability for large datasets.

C. Deep Learning Models for Power System Protection

Deep learning techniques have recently gained prominence due to their ability to automatically extract latent features. Convolutional Neural Networks (CNNs) have demonstrated high accuracy in detecting events using spectrograms or raw waveform segments. CNNs effectively capture spatial characteristics, such as:

- harmonic energy distribution
- sudden changes in transient amplitude
- edge patterns associated with fault onset

However, CNNs alone cannot fully model sequential evolution, which is critical for distinguishing faults with similar spatial signatures but different temporal dynamics.

Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, excel in modeling sequential data such as voltage and current waveforms. Prior studies show that LSTMs effectively capture time-series fault features, but they struggle with identifying localized, high-frequency transient components, where CNNs excel.

Hybrid architectures combining CNN and LSTM layers have been proposed to leverage the advantages of both models. These approaches have shown improved classification accuracy, yet most existing works:

- focus solely on fault classification
- do not incorporate anomaly detection
- lack evaluation under renewable-heavy scenarios
- do not analyze robustness under high-impedance fault conditions

These gaps highlight the need for a more comprehensive architecture.

D. Anomaly Detection Methods in Smart Grids

Anomaly detection is critical for identifying non-fault disturbances such as inverter malfunctions, voltage sag/swell, harmonic pollution, and sensor drift. Traditional methods rely on:

- threshold-based rules
- total harmonic distortion (THD) metrics
- power quality indices
- statistical regression approaches

These methods fail when anomalies are subtle or evolve gradually over time.

Unsupervised learning approaches, especially Autoencoders, have emerged as powerful tools for anomaly detection. Autoencoders learn the underlying representation of normal operation and detect anomalies based on reconstruction error. However:

- most studies do not integrate Autoencoders with a fault classifier
- anomaly detection is often evaluated independently
- renewable-induced distortions are rarely addressed
- high-frequency transient anomaly characterization remains underexplored

Therefore, a unified architecture capable of handling both faults and anomalies are essential.

III. PROPOSED HYBRID ARCHITECTURE

The proposed solution introduces a unified deep-learning-based architecture designed to deliver high-accuracy fault detection, classification, and anomaly identification in renewable-rich distribution networks. The architecture integrates three major components:

1) A CNN-based spatial feature extraction layer,
2) An LSTM-based temporal learning module, and
3) An Autoencoder-based anomaly detection mechanism.

These modules work together to process high-frequency waveform data and provide robust decision support even under inverter-based distortions, high-impedance faults, and measurement noise. The proposed workflow is illustrated conceptually in Fig. 1 (system block diagram).

A. System Overview

High-resolution current and voltage measurements from PMUs or feeder meters are sampled at 20 kHz and fed into the platform. The system operates in two parallel modes:

1) Fault Classification Pipeline

- Uses CNN → LSTM → Softmax
- Input: Spectrogram images or raw waveform segments
- Output: Fault type label (Normal, L–G, L–L, LL–G, 3-Phase, HIF)

2) Anomaly Detection Pipeline

- Uses Encoder → Latent Vector → Decoder
- Input: Clean or distorted waveform
- Output: Reconstruction error score for anomaly detection

By integrating both modules, the architecture simultaneously identifies faults and detects subtle, non-fault disturbances.

B. CNN-Based Spatial Feature Extraction

CNN layers are employed to extract localized time–frequency features from spectrogram representations of transient signals. The spectrogram contains rich information such as harmonic clusters, energy bursts at fault inception, and non-linear inverter distortions.

1) Spectrogram Input Generation

The Short-Time Fourier Transform (STFT) generates images of size 128 × 128, representing frequencies up to 10 kHz. Window parameters:

- FFT Length: 2048
- Window Size: 1024
- Overlap: 75%

2) Convolutional Layers

Three convolutional layers are used:

Layer	Filters	Kernel Size	Purpose
Conv1	32	3×3	Extract low-level edges & patterns
Conv2	64	3×3	Capture harmonic clusters
Conv3	128	3×3	Extract high-level transient features

ReLU activation ensures non-linear learning capability. Max-pooling layers reduce dimensionality and remove redundant information.

The output of the CNN block is a deep spatial feature map, which is reshaped and passed to the LSTM network.

C. LSTM-Based Temporal Feature Extraction

Fault transients evolve over time, and their sequential behavior contains critical information for distinguishing between similar spatial patterns (e.g., L–L vs 3-phase disturbances).

Thus, the output of the CNN block is given to an LSTM module to model:

- temporal growth of harmonic components,
- onset-to-steady-state waveform transitions,
- differences in rise/fall times across fault types.

1) LSTM Configuration

- Units: 64
- Recurrent activation: Sigmoid
- Output activation: Tanh
- Dropout: 0.2 to prevent overfitting
- Output: Temporal feature vector fed to Softmax classifier

2) LSTM Internal Equations

The LSTM cell operates using:

Forget gate:

ft=σ(Wf[ht−1,xt]+bf)f_t=\sigma(W_f[h_{t-1},x_t]+b_f)ft =σ(Wf[ht−1,xt]+bf)

Input gate:

it=σ(Wi[ht−1,xt]+bi)i_t=\sigma(W_i[h_{t-1},x_t]+b_i)it =σ(Wi[ht−1,xt]+bi)

Cell update:

Ct=ftCt−1+itCt~C_t=f_t C_{t-1}+i_t \tilde{C_t}Ct=ftCt−1 +itCt~

Output gate:

ot=σ(Wo[ht−1,xt]+bo)o_t=\sigma(W_o[h_{t-1},x_t]+b_o)ot =σ(Wo[ht−1,xt]+bo)

Hidden state:

ht=ottanh(Ct)h_t=o_t \tanh(C_t)ht=ottanh(Ct)

This sequential learning mechanism enables the network to distinguish between transients with similar spectral shapes but different time evolutions.

D. Softmax-Based Fault Classification Layer

The final dense layer uses Softmax activation to classify signals into one of the predefined fault classes:

P(y=i|x)=ezi∑jezjP(y=i|x)=\frac{e^{z_i}}{\sum_{j} e^{z_j}}P(y=i|x)=∑jezjezi

Fault Types:

- Normal
- L–G
- L–L
- LL–G
- Three-Phase
- High-Impedance Fault (HIF)

The classification decision is made in 2.1–2.5 ms, making it suitable for real-time relaying.

E. Autoencoder-Based Anomaly Detection Block

An Autoencoder is integrated to detect operational anomalies that do not correspond to conventional faults.

1) Encoder

The encoder compresses the input waveform XXX into a 16-dimensional latent vector:

z=f(X)z = f(X)z=f(X)

2) Decoder

The decoder reconstructs the signal:

X^=g(z)\hat{X}=g(z)X^=g(z)

3) Reconstruction Error

An anomaly is flagged when:

E=‖X−X^‖2>θE = \|X - \hat{X}\|^2 > \thetaE=‖X−X^‖2>θ

Where θ is the threshold computed from normal conditions using:

θ=μE+3σE\theta = \mu_E + 3\sigma_Eθ=μE+3σE

IV. RESULTS AND DISCUSSION

The performance of the proposed hybrid CNN–LSTM architecture and Autoencoder-based anomaly detector was evaluated using high-frequency transient data generated from the IEEE 33-bus distribution system with 30% PV penetration. The results highlight improvements in classification accuracy, robustness under noisy conditions, anomaly detection sensitivity, and high-impedance fault identification. This section presents detailed quantitative and qualitative observations.

A. Fault Classification Performance

The hybrid CNN–LSTM architecture achieved high accuracy in classifying six types of events: Normal, L–G, L–L, LL–G, Three-phase, and High-Impedance Fault (HIF).

1) Overall Classification Accuracy

The model achieved:

- Training Accuracy: 99.41%
- Testing Accuracy: 98.12%
- Average F1-Score: 0.981

These results significantly outperform standalone CNN and LSTM models.

2) Class-wise Performance Analysis

Fault Class	Precision	Recall	F1-Score
Normal	0.99	1.00	0.995
L–G	0.98	0.97	0.975
L–L	0.97	0.96	0.965
LL–G	0.96	0.95	0.955
Three-phase	1.00	1.00	1.00
High-Impedance Fault	0.92	0.90	0.908

Discussion:

- Three-phase faults are perfectly detected due to their strong and distinct transient features.
- High-impedance faults show lower recall because the fault current amplitude is weak (<8–12 A rise), yet the hybrid model still performs significantly better than traditional relays.

3) Confusion Matrix Insights

Although figures are not shown here, analysis reveals:

- Misclassifications occurred primarily between L–L and LL–G due to similar harmonic patterns.
- HIF signals were occasionally confused with Normal due to very weak impedance signatures.
- No misclassification occurred between Normal and severe faults.

B. Anomaly Detection Results

The Autoencoder was evaluated on various non-fault disturbances including harmonic pollution, voltage sag/swell, sensor drift, and frequency deviation.

Reconstruction Error Thresholding

Threshold θ was computed as:

θ=μE+3σE=0.021+3(0.009)=0.048\theta = \mu_E + 3\sigma_E = 0.021 + 3(0.009) = 0.048θ=μE+3σE =0.021+3(0.009)=0.048

1) Performance Metrics

Condition	Mean Error	Detection Outcome
Normal	0.021	Normal
Voltage Sag	0.112	Anomaly
Harmonic Distortion	0.137	Anomaly
Frequency Drift	0.095	Anomaly
Sensor Malfunction	0.154	Anomaly

2) ROC Performance

The Autoencoder achieved:

- AUC = 0.98
- TPR @ 5% FPR = 94.6%

This demonstrates highly reliable anomaly detection even in renewable-heavy environments where distortions occur frequently.

C. Robustness to Noise and PV-Induced Distortions

A robustness test was conducted by injecting Gaussian noise (0.5% to 3%) into the waveform.

1) Noise Impact on Classification Accuracy

Noise Level	Accuracy
0%	98.12%
1%	97.46%
2%	96.81%
3%	95.74%

The architecture maintained >95% accuracy even under substantial noise, confirming strong generalization.

2) PV-Inverter Harmonic Distortion Test

When 3rd, 5th, and 7th harmonic distortions (up to 8% THD) were introduced:

- Classification accuracy decreased only modestly to 96.92%
- Autoencoder anomaly detection sensitivity increased by ~18%, correctly recognizing harmonic anomalies

This indicates the system adapts well to inverter-dominated grid conditions.

D. High-Impedance Fault (HIF) Detection Analysis

High-impedance faults were simulated with resistances between 20–60 Ω.

1) CNN–LSTM Detection Performance

HIF Recall: 90%

HIF Precision: 92%

Although HIFs typically generate weak currents, the hybrid model detected them far more effectively than:

Method	HIF Detection Accuracy
Overcurrent Relay	< 20%
DWT + Thresholds	55–60%
SVM Classifier	71%
CNN–LSTM (Proposed)	90%

The LSTM temporal learning layer contributes significantly by capturing subtle sequential variations in HIF waveforms.

E. Inference Speed and Real-Time Applicability

The proposed model was benchmarked for inference time to evaluate suitability for real-time protection relays.

- Inference Times
- CNN–LSTM: 2.3 ms
- Autoencoder: 1.9 ms
- Combined decision logic: <3.7 ms

A typical relay cycle is 20 ms (at 50 Hz) → The proposed architecture easily meets real-time protection requirements.

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