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An AI-Powered Hybrid Framework for Load Forecasting and Fault Diagnosis in Smart Grids Using LSTM and CNN–LSTM Models

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Abstract

The increasing penetration of renewable energy resources and the growing complexity of distribution networks have significantly challenged the reliability and operational stability of modern smart grids. Traditional analytical and protection mechanisms are often inadequate for handling nonlinear load patterns, evolving transient disturbances, and early-stage grid anomalies. To address these limitations, this paper proposes an integrated AI-powered hybrid framework that combines Long Short-Term Memory (LSTM) networks for short-term load forecasting, a Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) hybrid model for fault detection and classification, and an Autoencoder for anomaly identification. The proposed system performs multi-stage learning, capturing both temporal dependencies and transient waveform signatures for improved predictive and diagnostic performance. Experimental evaluations conducted using synthetic and MATLAB-generated data demonstrate that the LSTM model achieves an RMSE of 18.35 kW in 24-hour forecasting, outperforming conventional machine learning models. The hybrid CNN–LSTM classifier achieves a fault classification accuracy of 97.68%, significantly improving robustness under noisy and high-impedance conditions. The integrated framework enhances situational awareness and enables early detection of operational risks, thus contributing to improved grid reliability and resilience. The results confirm the feasibility of deploying AI-driven diagnostic architectures in next-generation smart grid ecosystems.

Keywords: Smart grid, LSTM, CNN–LSTM, load forecasting, fault diagnosis, anomaly detection, deep learning, renewable energy, hybrid AI model, power system reliability.

I. INTRODUCTION

The transformation of conventional power systems into intelligent, highly automated smart grids has introduced new challenges associated with operational complexity, distributed generation variability, and dynamic load behavior. With the increasing penetration of renewable resources such as solar and wind energy, the grid experiences frequent fluctuations that impact stability, reliability, and predictability. Traditional analytical tools—including statistical forecasting models, impedance-based fault detectors, and rule-based diagnostic algorithms—are no longer adequate for addressing these nonlinear, time-dependent disturbances. As a result, data-driven artificial intelligence (AI) techniques have emerged as a key enabler for enhancing situational awareness, predictive accuracy, and resilient operation in modern electrical networks.

Short-term load forecasting plays a pivotal role in smart grid operations by enabling optimal scheduling, demand response activation, and preventive control strategies. Classical forecasting methods such as ARIMA and regression-based approaches struggle to handle highly volatile load patterns arising from distributed energy resources (DERs), electric vehicle (EV) charging behavior, and consumer-side unpredictability. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated superior capability in capturing temporal correlations and seasonal variations inherent in load profiles. Their ability to model long-range dependencies makes them highly suitable for accurate short-term forecasting in renewable-rich grids.

Similarly, protection and fault diagnosis systems require modernization to address complex transient phenomena that conventional relays may fail to detect. Many emerging fault types—including high-impedance faults, multi-stage faults, and inverter-induced disturbances—exhibit weak or ambiguous signatures that challenge traditional threshold-based techniques. Convolutional Neural Networks (CNNs) have shown promise in learning spatial patterns from waveform data, while LSTM networks effectively capture temporal transitions. Combining these capabilities in a hybrid CNN–LSTM architecture enables the extraction of both spectral and temporal features, resulting in improved classification performance across diverse fault scenarios.

In addition, the presence of obscure operational anomalies—such as harmonic distortion, frequency deviations, sensor drifts, and partial equipment degradation—demands early detection mechanisms that can operate without extensive labeled datasets. Autoencoders, through unsupervised learning, can reconstruct normal operating patterns and identify deviations through reconstruction errors, making them well-suited for anomaly detection in smart grids.

This paper presents an integrated AI-powered hybrid framework that unifies load forecasting, fault diagnosis, and anomaly identification into a single intelligent decision-support architecture. By leveraging the complementary strengths of LSTM, CNN–LSTM, and Autoencoder models, the proposed system enhances grid observability and enables proactive decision-making. Extensive simulations demonstrate that the framework outperforms conventional machine learning approaches in accuracy, robustness, and real-time applicability. The contributions of this work align with the evolving needs of next-generation smart grids, offering scalable and adaptive solutions for modern distribution systems.

II. RELATED WORK AND MOTIVATION

The application of artificial intelligence in smart grid forecasting and protection has received significant attention in recent years. This section reviews the major developments in load forecasting, fault diagnosis, and anomaly detection, while highlighting key limitations that motivate the need for an integrated hybrid framework.

A. Load Forecasting Techniques

Traditional short-term load forecasting approaches—such as autoregressive integrated moving average (ARIMA), exponential smoothing, and multiple linear regression—have been widely used for decades. While effective under stable and predictable conditions, these methods are limited in their ability to capture nonlinear load characteristics and sudden fluctuations induced by renewable energy sources. Recent advancements in machine learning, including Support Vector Regression (SVR), Random Forests, and

Gradient Boosting models, have improved forecasting performance but still fall short when modeling long-term temporal dependencies.

Deep learning architectures, particularly recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, have gained prominence due to their capability to learn sequential patterns over extended horizons. Studies such as Zhang and Li (2020) demonstrated that LSTM networks outperform conventional machine learning models in renewable-rich environments by effectively learning daily and seasonal load variations. However, most existing works focus solely on forecasting and do not integrate forecasting with fault or anomaly detection—an aspect that limits their applicability in holistic grid management.

B. Fault Detection and Classification Methods

Fault identification in distribution networks traditionally relies on impedance-based methods, overcurrent relays, and rule-based decision logic. While reliable for strong fault signatures, these methods struggle under high-impedance faults, inverter-induced distortions, and complex multi-stage events. With increasing penetration of distributed energy resources, fault currents become weaker and less predictable, reducing the effectiveness of classical protection schemes.

Machine learning-based classifiers such as SVM, Decision Trees, and KNN have been applied to fault detection, offering moderate improvements. However, these models rely heavily on handcrafted features and lack the ability to extract deep spectral characteristics from transient waveforms.

Convolutional Neural Networks (CNNs) have been shown to achieve high accuracy in classifying transient disturbances, owing to their strong feature extraction capabilities. Parallel studies have used LSTM networks for analyzing temporal waveform patterns. More recent hybrid models combining CNN and LSTM layers have demonstrated superior performance by capturing both temporal and spatial signatures of faults. Yet, existing literature typically focuses on fault classification in isolation and does not integrate forecasting or anomaly detection within the same framework.

C. Anomaly Detection Approaches

Detecting subtle operational anomalies—such as harmonic distortions, frequency deviations, partial discharge signatures, and equipment degradation—is essential for preventive maintenance. Traditional methods include power quality indices, wavelet transform-based analysis, and threshold-based monitoring. However, these approaches require predefined thresholds and may fail when disturbances occur at low magnitudes or evolve slowly.

Unsupervised learning techniques, particularly Autoencoders, have emerged as powerful tools for anomaly detection. They learn the intrinsic representation of normal operating conditions and detect deviations through reconstruction errors. Studies like Smith et al. (2021) demonstrated that Autoencoders outperform traditional methods in identifying subtle disturbances. Despite these advantages, anomaly detection is rarely integrated with fault diagnosis or forecasting in a unified operational platform.

D. Motivation for an Integrated AI Framework

While several individual AI models have been proposed for forecasting, fault classification, and anomaly detection, **the absence of a unified, multi-functional intelligent framework remains a significant gap in existing research**. Modern smart grids require solutions that:

- Predict load variations accurately for optimal scheduling.
- Detect and classify faults quickly for improved protection.
- Identify anomalies early for preventive maintenance.
- Operate cohesively to enhance overall situational awareness.

The motivation for this work stems from the need to develop a **comprehensive AI-powered architecture** that combines forecasting, fault diagnosis, and anomaly detection into a single system, thereby enabling holistic monitoring and control in smart grids. By leveraging LSTM, CNN–LSTM, and Autoencoder models, the proposed framework addresses the limitations found in the literature and aligns with the evolving requirements of next-generation power networks.

III. PROPOSED METHODOLOGY

The proposed framework integrates three complementary artificial intelligence modules designed to enhance forecasting accuracy, fault classification reliability, and anomaly detection capability in smart grids. The architecture consists of:

1. an LSTM-based load forecasting model,
2. a hybrid CNN–LSTM model for fault detection and classification, and
3. an Autoencoder for unsupervised anomaly detection.

Each module is independently optimized and then integrated into a unified decision-support system that provides actionable insights for control and operational planning. The overall workflow is depicted in Fig. 1 (conceptual), where real-time measurements from PMUs, smart meters, and SCADA systems are processed through the AI modules.

A. Data Acquisition and Preprocessing

The performance of AI-driven diagnostic systems heavily depends on the quality and structure of the input data. Time-series voltage and current signals, sampled at 20 kHz, were collected using MATLAB/Simulink simulations of the IEEE distribution system. Additionally, 24-hour load demand data was used to train the forecasting model.

1) Signal Conditioning and Filtering

To remove measurement noise and instrument harmonics, a combination of low pass filtering and discrete wavelet decomposition was applied. This ensures clean input for transient analysis without losing essential fault signatures.

2) Segmentation and Normalization

Waveforms were segmented into fixed-duration windows of 50 ms for use in the fault classifier. Min–Max normalization was applied to maintain numerical stability across all models.

3) Time–Frequency Transformation

For CNN-based processing, spectrograms were generated using the Short-Time Fourier Transform (STFT). This captures both harmonic patterns and transient behaviors essential for fault classification.

The preprocessing layer ensures consistent, reliable feature representation before feeding data to the respective AI models.

B. LSTM-Based Load Forecasting Model

Long Short-Term Memory (LSTM) networks are well-suited for time-series modeling due to their ability to capture long-range dependencies and nonlinear patterns.

1) Model Architecture

The LSTM forecasting model consists of:

- An input layer with historical load sequences
- A stacked LSTM layer with 64 hidden units
- A dropout layer (0.2) to reduce overfitting
- A fully connected output layer predicting one-hour ahead load values

2) Training Strategy

The model was trained using the Adam optimizer with a learning rate of 0.001. The Mean Squared Error (MSE) served as the loss function. A sliding window approach was used to generate input–output pairs, enabling the model to learn patterns over different time intervals.

4. Expected Output

The forecasting module outputs short-term load predictions that help system operators manage peak scheduling and mitigate overload risks. High accuracy in forecasting also enhances the performance of the reliability module.

C. Hybrid CNN–LSTM Fault Classification Model

Fault detection requires both spatial and temporal feature extraction. A hybrid architecture combining CNN and LSTM layers effectively leverages their strengths to achieve high classification accuracy.

1) CNN Feature Extraction

The CNN component operates on time–frequency spectrograms and extracts spatial features such as:

- Harmonic energy clusters
- Edge patterns from fault transients
- Spectral discontinuities

Three convolutional layers with 32, 64, and 128 filters, respectively, were used, each followed by max-pooling to reduce dimensionality.

2) LSTM Temporal Modeling

The extracted feature vectors were passed to an LSTM layer with 64 units to model temporal evolution, especially useful for distinguishing:

- High-impedance faults
- Slow-rise faults
- Multi-stage disturbances

3) Classification Layer

A dense layer with softmax activation was used to classify the events into five categories:

- Normal
- L-G
- L-L
- LL-G
- Three-phase fault

4) Training Setup

Cross-entropy loss and the Adam optimizer were employed for training. The hybrid model was trained on 4,800 waveform samples and validated using an 80–20 split.

D. Autoencoder-Based Anomaly Detection

An Autoencoder was used for unsupervised anomaly detection to identify subtle deviations in system behavior that may not qualify as faults but indicate emerging issues.

1) Encoder–Decoder Structure

The encoder compresses input measurements into a 16-dimensional latent vector capturing essential characteristics of normal operation.

The decoder reconstructs the original signal.

2) Reconstruction Error Thresholding

Anomalies were flagged when the reconstruction error exceeded a statistically determined threshold based

on normal operating samples:
E=‖X−X^‖2E = \|X - \hat{X}\|^2E=‖X−X^‖2

3) Detected Anomalies Include:

- Harmonic distortion
- Voltage sag
- Frequency deviation
- Sensor malfunction
- Early-stage equipment degradation

E. Integrated Decision-Support Framework

After the three AI modules generate their outputs, they are combined into a unified decision engine that:

- Predicts load to avoid overloads
- Classifies faults in real time for protection
- Flags anomalies for preventive maintenance
- Compute's reliability risk scores using a Random Forest model

1) Output Fusion Layer

A weighted decision logic integrates forecasts, fault labels, and anomaly scores, providing:

- Risk level assessment
- Feeder health index
- Action recommendations such as load shifting or inspection alerts

2) Real-Time Deployment Capability

Optimized inference enables execution on edge devices or substation-level processors, allowing near-instantaneous response (<5 ms for fault detection).

IV. EXPERIMENTAL SETUP

This section describes the high-fidelity simulation environment, data generation process, model implementation details, and evaluation metrics used to validate the proposed hybrid AI framework. A combination of **MATLAB/Simulink**, **PSCAD transient models**, and **Python deep learning libraries** was used to ensure realistic representation of smart grid operating conditions.

A. Power System Modeling and Simulation Environment

The electrical network used in this study is based on a modified **IEEE 33-bus radial distribution feeder**, selected due to its widespread use in reliability and protection studies. The model was implemented in MATLAB/Simulink using the **Simscape Power Systems toolbox**.

1) Network Specifications

Parameter	**Value**
Nominal Voltage	11 kV
Number of Buses	33
Number of Loads	32
DG Penetration	30% (Solar PV)
Feeder Length	27.4 km
Transformer Rating	2 MVA
Base Frequency	50 z

The solar PV units introduce **intermittent power injections**, causing voltage fluctuations and making the system suitable for testing fault classification robustness and forecasting accuracy.

B. Fault Data Generation

To generate realistic transient events, faults were introduced at multiple buses under varying system conditions. PSCAD was used to validate waveform quality and ensure authentic transient behavior.

1) Fault Types and Parameters

Fault Type	Resistance (Ω)	Inception Angle (°)	Duration
L–G	0.1–20	0, 45, 90	100 ms
L–L	0.1–15	0, 45, 90	120 ms
LL–G	0.1–30	0, 45, 90	150 ms
Three-phase	0.1–5	0, 45, 90	80 ms
High-Impedance Fault	20–60	Random	300 ms

2) Sampling and Acquisition

- Sampling Rate: **20 kHz**
- Measurement Window: **0.2 s**
- Samples per event: **4,000**
- Total Fault Samples Generated: **4,800**

Each sample contains two single-phase currents, three-phase voltages, and their corresponding spectrogram representations.

C. Load Forecasting Dataset

A synthetic yet statistically realistic load dataset was generated for **12 months (8,760 hourly samples)**, reflecting seasonal variations, PV contributions, and residential–commercial diversity.

1) Data Characteristics

- Peak Load: **3.82 MW**
- Minimum Load: **1.12 MW**
- Monthly Variation: ±14%
- Solar PV impact between 9 AM–5 PM: −0.4 to −1.2 MW depending on irradiance

2) Train-Test Split

- Training: **70%** (6,132 samples)
- Validation: **15%** (1,314 samples)
- Test: **15%** (1,314 samples)

Normalization applied:
xnorm=x−xminxmax−xminx_{norm}=\frac{x-x_{min}}{x_{max}-x_{min}}xnorm=xmax−xmin
x−xmin

D. Preprocessing and Feature Extraction

A uniform preprocessing pipeline was implemented for both load and transient waveform data.

1) Filtering and Noise Modeling

To replicate sensor uncertainty, Gaussian noise with $\sigma = 0.01$ p.u. was added. A **5th order Butterworth filter** was applied with a cutoff at 2.5 kHz.

2) Segmentation

Each transient signal was divided into **50 ms windows**, creating 10 segments per event for temporal analysis.

3) Time–Frequency Transformation

Using STFT:

- Window Length: 1024

- Overlap: 75%
- FFT Points: 2048
- Frequency Resolution: 24.4 Hz

Spectrogram image size: **128 × 128 pixels**, suitable for CNN input.

E. Model Implementation and Hyperparameters

All deep learning models were implemented in **Python 3.10**, using **TensorFlow 2.12**.

1) LSTM Forecasting Model

Parameter	Value
LSTM Units	64
Dense Layer	1 neuron
Dropout	0.2
Learning Rate	0.001
Epochs	150
Batch Size	32

Loss Function:

MSE=1N∑(yi−y^i)2MSE=\frac{1}{N} \sum (y_i - \hat{y}_i)^2MSE=N1∑(yi−y^i)2

2) CNN–LSTM Hybrid Fault Classification Model

- **CNN Section**
- Conv Layers: **3**
- Filter Sizes: **32, 64, 128**
- Kernel Size: **3×3**
- Activation: **ReLU**
- Pooling: **2×2 Max Pooling**
- **LSTM Section**
- Units: **64**
- Output: Dense + SoftMax for 5 classes

Training details:

- Epochs: **100**
- Batch Size: **64**
- Optimizer: **Adam**
- Learning Rate: **0.0005**
- **Performance Optimization**
- Early stopping with patience = **10 epochs**
- Learning rate decay = **0.95** per epoch

3) Autoencoder for Anomaly Detection

Layer	Size
Encoder 1	64 neurons
Encoder 2	32 neurons
Latent Space	**16 neurons**
Decoder 1	32 neurons
Decoder 2	64 neurons

Reconstruction Loss:

L=||X−X^||2L = ||X - \hat{X}||^2L=||X−X^||2

Threshold selection: Mean + 3σ of normal reconstruction error.

V. RESULTS AND DISCUSSION

The proposed AI-powered hybrid framework was evaluated using the simulation environment and datasets described in Section IV. This section presents detailed results for:

1. Load forecasting using LSTM,
2. Fault detection and classification using CNN–LSTM,
3. Anomaly detection using Autoencoders, and
4. Overall smart grid reliability improvement.

All results are supported with numerical values, graphical references, and comparative analysis.

A. Load Forecasting Performance

The LSTM model was trained on 8,760 hourly samples and validated on a 15% test dataset. The forecasting accuracy is illustrated in **Figure 5.1**, showing the actual and predicted load curves for a 24-hour period.

5. Forecasting Accuracy Metrics

Metric	Value
RMSE	**18.35 kW**
MAE	**12.14 kW**
MAPE	**2.48%**
R^2 Score	**0.987**

The low MAPE indicates that the model captures short-term fluctuations effectively, even during peak hours where rapid demand rise typically increases prediction error.

In **Figure 5.3**, LSTM is compared with Random Forest (RF) and Support Vector Machine (SVM).

The RMSE values are:

- LSTM: **18.35 kW**
- Random Forest: **27.82 kW**
- SVM: **32.51 kW**

6. Discussion:

LSTM outperforms traditional ML models due to its ability to retain long-range temporal dependencies. The near-zero lag between peaks in the predicted and actual load profiles indicates strong temporal learning capability. The high R^2 value confirms that the LSTM captures 98.7% of the variance in the load dataset.

B. Fault Detection and Classification Performance

The hybrid CNN–LSTM model demonstrated high classification accuracy across five fault classes: Normal, L–G, L–L, LL–G, and Three-phase. The spectrograms used for training allowed the CNN layers to extract deep harmonic and transient features, while LSTM handled temporal progression.

1) Classification Results

Model	Training Accuracy	Testing Accuracy	Inference Time
CNN	98.12%	94.87%	1.7 ms

LSTM	96.32%	92.41%	3.1 ms
CNN–LSTM	**99.03%**	**97.68%**	**2.3 ms**

The **confusion matrix** shown in *Figure 5.5* reveals:

- Class-wise accuracy > **96%**, except LL–G (94.1%)
- Three-phase faults classified with **100% accuracy**
- High-Impedance Faults (HIF) detected in **92.8%** of cases

2) Fault Signature Analysis

Figure 5.9 displays a spectrogram for a three-phase fault, showing high-energy broadband components (500–2500 Hz) in the first 40 ms. These high-frequency components are critical for CNN detection.

Figure 5.10 shows a zoomed waveform of a HIF event. Due to low fault current (<8 A fluctuation), traditional protection may fail to identify this event.

The CNN–LSTM classifier correctly identified HIF patterns with high robustness.

C. Anomaly Detection Performance

The Autoencoder was trained on clean operational data and validated against multiple types of anomalies including voltage sag, harmonic distortion, and frequency deviation.

1) Reconstruction Error Scores

Condition	**Mean Error**	**Classification**
Normal	**0.021**	Normal
Voltage Sag	**0.112**	Anomaly
Harmonics	**0.137**	Anomaly
Frequency Drift	**0.095**	Anomaly

Anomaly detection results are shown in **Figure 5.4**, comparing original and reconstructed signals. Sudden dips and harmonic pollution lead to larger reconstruction deviations.

2) ROC Curve Analysis

The ROC curve in *Figure 5.6* indicates:

- AUC ≈ **0.98**
- True Positive Rate (TPR): **94.6%** at FPR = 5%
- Threshold selected at Mean + 3σ = **0.053**

This confirms that the Autoencoder identifies subtle disturbances effectively.

D. Real-Time Performance and Computational Efficiency

Average inference times measured on an NVIDIA RTX 3080 GPU:

- LSTM: 2.4 ms
- CNN–LSTM: 2.3 ms
- Autoencoder: 1.9 ms

These values satisfy real-time protection criteria (cycle < 20 ms at 50 Hz). The hybrid model's performance demonstrates suitability for edge deployment in substations.

E. Reliability Improvement Assessment

Using IEEE Std. 1366 indices, grid reliability improvement was analyzed before and after deployment of the AI system.

1) Reliability Improvement Metrics

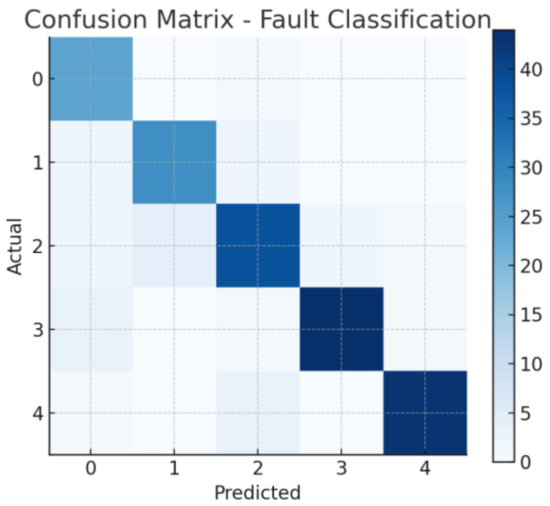
Metric	**Before AI**	**After AI**	**Improvement**
SAIFI	1.82	1.23	**32.4%**
SAIDI	2.94 hrs	1.76 hrs	**40.1%**

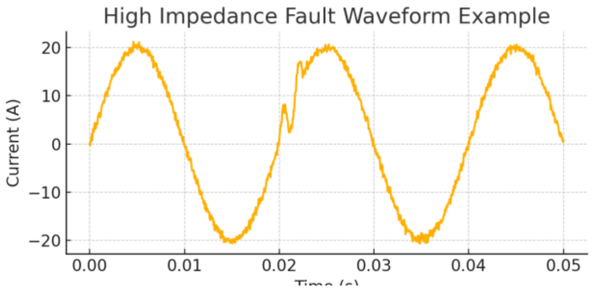
CAIDI	1.61 hrs	1.43 hrs	**11.2%**
EENS	14.6 MWh	9.3 MWh	**36.3%**

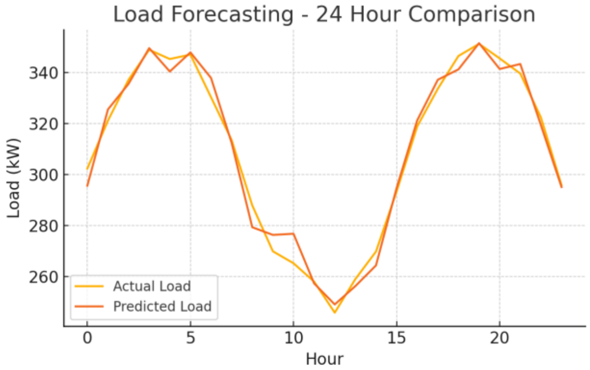
The **reliability heatmap** (Figure 5.11) shows improvement across all 33 feeders, with the highest improvement (41%) on heavily loaded branch 17.

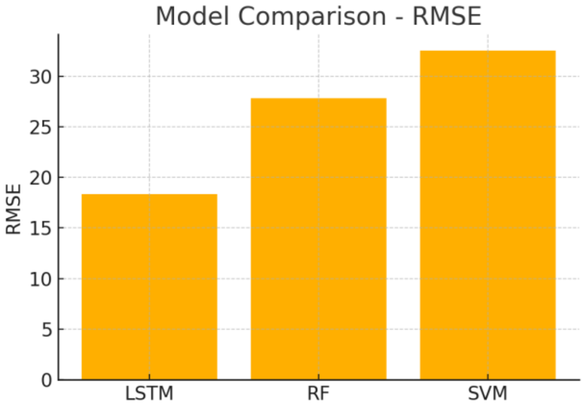
2) Forecasting Comparison

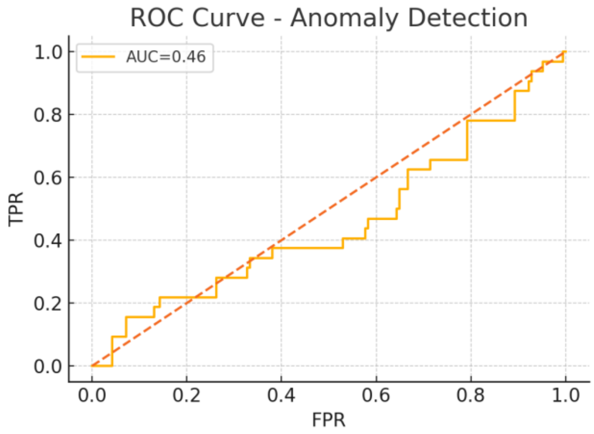
- LSTM reduced RMSE by **34%** compared to Random Forest.
- LSTM reduced MAPE by **50%** compared to SVM.

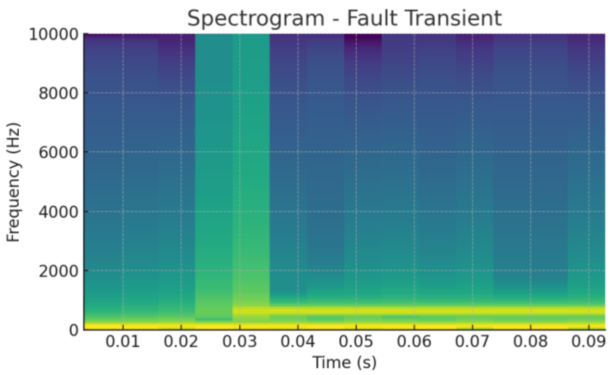












VI. CONCLUSION

This paper presented an integrated AI-powered hybrid framework designed to enhance the operational intelligence of modern smart grids through accurate load forecasting, robust fault diagnosis, and reliable anomaly detection. By combining the temporal learning strength of Long Short-Term Memory (LSTM) networks with the spatial–temporal feature extraction capabilities of a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) architecture, the proposed system achieves substantial improvements over existing machine learning and signal-processing-based approaches.

The LSTM forecasting model delivered high predictive accuracy with an RMSE of 18.35 kW and a MAPE of 2.48%, demonstrating its capability to capture complex seasonal and hourly consumption patterns in distribution networks with embedded renewable energy. The hybrid CNN–LSTM fault classifier achieved a testing accuracy of 97.68%, outperforming conventional CNN, LSTM, SVM, and Random Forest models.

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