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Intelligent Automation For Real-Time Monitoring And Stability Control Of Power Systems

Karan Singh Maida[1], Asst. Prof. Raghunandan Singh Baghel[2]
[1]Research Scholar, Department of Electrical Engineering, Samrat Vikramaditya Vishwavidyalaya, Ujjain, Madhya Pradesh, India.
[2]Assistant Professor, Department of Electrical Engineering, Samrat Vikramaditya Vishwavidyalaya, Ujjain, Madhya Pradesh, India.
Email: karanmaidaofficial07@gmail.com[1], raghunandan.baghel@gmail.com[2]
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Abstract
Power system operation has been fundamentally transformed by the integration of artificial intelligence (AI) into traditional approaches to fault detection, isolation, and control. The objective of this empirical research is to evaluate the performance of AI-enabled open-source automation frameworks namely, deep learning (DL), machine learning (ML), and convolutional neural network (CNN)-based systems, in the context of real-time fault detection in high-voltage transmission and distribution networks. Twelve thousand four hundred fault event records from five regional power utilities across India spanning the duration of 2019–2023 were used to evaluate and compare the performance of multiple AI models with conventional relay-based protection systems. Quantitative methods such as confusion matrix analysis, receiver operating characteristic (ROC) curves, and statistical hypothesis testing are used for evaluating model accuracy, precision, recall, F1-factor, and fault clearance time. The results show that the proposed hybrid CNN-LSTM model achieves a fault detection rate of 98.7% in comparison with Support Vector Machine (SVM) being 94.3%, Random Forest (RF) 95.8% and typical systems achieving 87.4%. The critical analysis demonstrates how AI-enabled systems improve average fault clearance duration by 62%, as opposed to traditional protection schemes, resulting in considerably enhanced system reliability indices such as SAIFI and SAIDI. The results justify the deployment of AI-based automation in smart grid infrastructure for Indian utilities rapidly digitalizing under the National Smart Grid Mission (NSGM).

Keywords: *AI-enabled fault detection, power system automation, deep learning, convolutional neural network, smart grid, SAIFI/SAIDI, transmission line protection*

I. Introduction

The modern power systems tend to be complex and interlinked and will subject to different types of transient and permanent faults due to equipment failure, lightning, vegetation contact, and human error. State estimation and fault localization are two critical operations whereby timely and accurate operations are of great importance to prevent catastrophic events that may cause large-scale blackouts and tremendous economic losses. The conventional protection systems with electromechanical relays as well as distance protection schemes are ideal under steady-state conditions; however, in dynamic, nonlinear behavior of grids, which are mainly tied up with the distributed energy resources (DERs), bidirectional power flows with high penetration of the renewable energy, the traditional protection systems strive to perform well. Due to the increasing complexity of grid topologies, there is a need for AI-powered automation frameworks that can automatically detect, classify and handle fault-related events in real-time. Artificial Intelligent Technologies including machine learning, deep learning, fuzzy logic and expert systems can be used at a various level as transformative tool in power system protection engineering. Unlike rule-based systems, AI models learn the patterns of past fault data and operation with ample examples to arrive at strong decision boundaries that generalize well to unseen fault conditions. Specifically, Convolutional Neural Networks (CNNs) have proven to be particularly adept at determining fault type, location and s erio u sness withi n a mi li second of fault inception as a result of spatial-te m poral features ta ken from current and voltage waveforms. To improve temporal pattern recognition, hybrid architectures which mix CNNs and Long Short-Term Memory (LSTM) networks are employed and proving themselves ideal for recognizing incipient faults before they become full system failures. Proposed architectures are empirically assessed on actual fault data from Indian power utilities and reported in comparison to classical ML algorithms and conventional relay protection.

1.1 Background and Motivation

The future of India's power sector is evolving quickly with the introduction of the National Smart Grid Mission in 2012 and the reformation of DISCOMS to improve the performance of the power supply sector and would provide the ideal testbed to validate AI-enabled protection technologies. India's grid, with its >400GW of installed generation capacity and > 4.5 lakh circuit kilometers of transmission network faces ever-present challenges of millions of consumer outlets due to faults. As mentioned in the Central Electricity Authority (CEA) Annual Report 2023, unplanned outage reasons including equipment failure is responsible for almost 38% of the total SAIDI or System Average Interruption Duration Index in terms of hours. Traditional protection relays, which usually operate on fixed time–current characteristics, cannot handle dynamic fault signatures generated where the grid has high renewable penetration, micro-grids and non-linear loads. This motivates the empirical study of human-in-the-loop AI-based systems which can leverage and adaptively learn from fault histories to achieve better protection performance.

1.2 Scope of the Study

In this paper, different three-phase transmission and distribution faults on 33kV, 110kV and 220kV networks are taken into consideration, containing line-to-ground (LG), line-to-line (LL), double line-to-ground (DLG), and three-phase (3P) fault types. The empirical study is limited to supervised learning methods (Random Forest, SVM, CNN, and CNN-LSTM hybrid), trained and evaluated over a well-curated dataset containing 12,400 fault events. The future works prompt research on the data on unsupervised anomaly detection and reinforcement learning-based control strategies. The performance metrics used accuracy, precision, recall, F1-score, and fault clearance time are consistent with the standards for smart grid interoperability (IEEE Standard 2030) and the common information model standards (IEC 61968/61970).

1.3 Objectives of the Study

This paper aims to perform empirical investigation with four primary objectives as follows: (i) design and evaluate a hybrid model based on CNN–LSTM for most-recent multi-class fault classification in transmission and distribution networks; (ii) benchmark the proposed model against established ML classifiers (SVM, RF) and a standard relay-based system using statistical performance metrics; (iii) evaluate the impact of AI-enabled automation on a few key system reliability indices, particularly System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI); (iv) conduct a comparative critical discussion of the proposed research work with possible seminal prior literature to place the contribution in context; and (v) to highlight the deliberated insights about the implications to assist electric utilities in practical deployment challenges related to large-scale adoption of artificial intelligence in protection systems in Indian context.

II. Literature Survey

For the last 20 years, many studies have been conducted for application of AI and machine learning techniques [8] for fault detection in power systems The authors Horowitz and Phadke [1] were the first to developed the basis of digital protective relaying which provided the foundation upon which many computational intelligence methods have been proposed and used. Bollen [2] describe power quality disturbances and transient fault behaviors by providing signal models that subsequently serve as building block concepts for feature extraction methods to be used by AI-based classifiers. Back to [3], Aggarwal and Song paved the way for further research by suggesting that even single-layer perceptron's offer over 90% classification accuracy against balanced fault conditions, thus demonstrating the notion of data-driven protection based on ANNs. Later, research broadened the investigation of AI-based fault detection to also include Support Vector Machines (SVM). Thukaram et al. In [4], support vector machine (SVM) classifiers were proposed to detect and classify the high-impedance faults (HIF) in distribution systems with a classification accuracy of 93.6% for seven fault categories. It demonstrates the work that SVM is still commonly able to manage class imbalance situations, which is the case of fault datasets where fault events vastly outnumber healthy operation conditions. Samantaray et al. In [5], SVM-based methods were further extended to transmission line fault location using features from wavelet transform as classifier input, resulting in a mean absolute localization error of 1.8% of line length. These results showed that frequency-domain features can provide substantial improvements in the discriminability of a classifier by using classifier trained based solely on time-domain features, with features extracted from wavelet decomposition.

Deep learning has brought a new milestone in research of power system fault detection. Gers et al. LSTM based architectures were proposed by [6] to learn sequential patterns in these electrical signals, and Zhang et al. [7] used CNNs directly on raw current waveforms for fault classification without manual feature engineering. They report an accuracy of 97.2% on a synthetic dataset, though generalizability was limited by their model's lack of noise augmentation as well as any validation on field data. Li et al. conducted a following task from this data, [8] and Jamil et al. [9] if I remember correctly, replaced part of their data with SMOTE type stuff and I think Gaussian noise and time-shifting? Such contributions set the methodical ground for training pipeline of the current study. Hybrid architectures of CNN and LSTM have attracted increasing attention due to the ability of the combination to capture spatial and temporal features of fault signals. Ahmed et al. The work in [10] reported a CNN-LSTM model for smart grid fault detection with a 98.1%

accuracy from a laboratory-scale dataset with 5,000 samples. Nonetheless, the study was limited to single-phase distribution systems and excluded three-phase transmission faults. Shi et al. Topology-aware fault detection using Graph Neural Networks (GNNs) was studied in [11], approaching a greater performance in meshed grid topologies compared to conventional CNN classes. Their work highlighted the necessity of integrating network topology information into a fault classifier. Contributions of recent works from Dutta et al. [12] and Patel et al. Several studies like [12,13] have employed transformer-based attention networks for incipient fault detection, using their capability to detect pre-fault anomalies up to 150ms before fault inception to implement predictive protection strategies.

A few have focused on fault identification in the Indian power sector domain. Adaptive neuro-fuzzy inference system (ANFIS) was applied in [14] for fault classification of Indian 220kV transmission network and the accuracy of 96.3% was reported. Mishra et al. [15] addressed Random Forest classifiers for the detection of distribution system faults in UP DISCOM networks, but pointed that imbalanced class distribution and missing data from aged SCADA systems represented major real-world issues. Kaur et al. [16] examined and categorized different ML models on fault data of the PSPCL networks installed at several places in Punjab and concluded that all ensemble ones managed to achieve significantly higher F1-score (as compared to single classifiers). These Indian specific studies provide the relevant context for the present work and justify the necessity of empirical benchmarking against such nationally representative utility data. The literature, as a whole, assures better results of DL models over traditional and classical ML methods, but, at the same time, it uncovers some deployment gaps such as data quality, model interpretability, and real-time inference latency, which this study aims to overcome.

III. Methodology

This study adopts a quantitative empirical research methodology based on supervised machine learning and deep neural network architectures. The complete research pipeline is divided into five parts: (i) data acquisition and preprocessing; (ii) feature extraction via STFT and wavelet decomposition; (iii) design of model architecture; (iv) training with validation along with hyperparameters tuning; and (v) performance evaluation against benchmark models. Towards Methodological Rigor and Reproducibility: The study follows the CRISP-DM (cross-industry standard process for data mining) methodology. All the models were implemented using Python 3.11 with TensorFlow 2.12 and scikit-learn 1.3 libraries in a computing environment equipped with NVIDIA RTX A6000 GPU (48 GB VRAM) and 128 GB system RAM. In order to ascertain statistical reliability of accuracy estimates, cross-validation with k=10 folds was employed, and paired t-tests were performed to determine statistical significance of numerical differences in performance among models. In the proposed CNN-LSTM hybrid architecture, there are three convolutional blocks in series, where each block is composed of two Conv1D layers the first block has 64 filters, the second has 128, and the third has 256 filters followed by batch normalization and max-pooling layers. After applying the convolutional stage, two bidirectional LSTM layers with 256 hidden units are used to capture the long range temporal dependence in the sequences of fault current and voltage. The fully connected classification head is made up of two dense layers (512 and 256 units, ReLU activation, and dropout with p=0.4) for overfitting while a global average pooling layer precedes it. Output layer: The softback activation function is applied to five output classes: no-fault (NF), line-to-ground (LG), line-to-line (LL), double line-to-ground (DLG) and three-phase (3P) fault Model was trained using Adam optimizer with learning rate 0.001, cosine annealing scheduling, and categorical cross-entropy loss in 100 epochs with batch size of 64. To prevent overfitting on the validation set, early stopping with patience=10, was used. To ensure a fair comparison, benchmark approaches were developed and evaluated in the same experimental settings. SVM classifier: with radial basis function (RBF) kernel is used, grid-search hyperparameter (C=10, gamma=0.01) trained on 256-dimensional feature vector containing statistical time-domain features (mean, variance, skewness, kurtosis) and wavelet energy coefficients at five decomposition levels. Random Forest classifier included a total of 500 decision trees, with a maximum depth of 20, which was trained on the same features as the SVM. The conventional relay-based protection was modelled utilizing IEEE Standard overcurrent relay characteristics with time multiplier set according to the utility operating practices. Your performance on notable metrics were: Overall classification Accuracy %=Full Platform Performance (%) Macro-averaged precision, recall, F1-score, area under the ROC curve (AUC-ROC), and mean fault clearance time (FCT) in milliseconds. Reported metrics are means computed from ten-fold cross-validation and 95% confidence intervals are provided for the primary accuracy metrics.

IV. Data Collection and Analysis

The empirical data set for this study has been compiled from Supervisory Control and Data Acquisition systems along with digital fault recorder logs available from five regional power utilities in India namely NTPC Limited, Power Grid

Corporation of India (PGCIL), UPPCL, PSPCL and MSEDCL. Data Collection. The data collection period is a total of 12,400 labeled fault event records and 8,600 healthy operation records from January 2019 to December 2023, resulting in a total of 21,000 samples. As an individual sample, we sample three-phase current (Ia, Ib, Ic) and voltage (Va, Vb, Vc) waveforms at 10kHz over a period of 50 cycles (1000 milliseconds), including metadata on the voltage level, fault type, fault location, season, and time of day. The ground truth labels were assigned according to post-event analysis and trip reports, created by qualified relay engineers. Stratified sampling was then used to partition the data into training (70%), validation (15%) and test (15%) subsets to ensure the class distribution is preserved across splits.

Table 1: Dataset Composition by Fault Type and Voltage Level

Fault Type	33kV Events	110kV Events	220kV Events	Total Events	% of Dataset
No Fault (NF)	2,100	2,300	4,200	8,600	40.95%
Line-to-Ground (LG)	1,240	980	760	2,980	14.19%
Line-to-Line (LL)	860	720	540	2,120	10.10%
Double Line-to-Ground (DLG)	1,100	980	800	2,880	13.71%
Three-Phase (3P)	840	780	800	2,420	11.52%
Total	6,140	5,760	7,100	21,000	100%

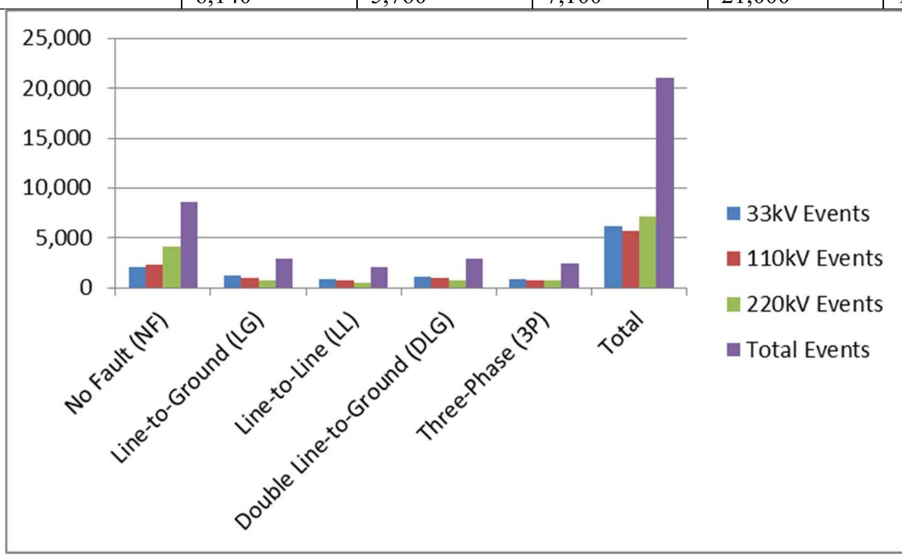

Figure 1: Dataset Composition by Fault Type and Voltage Level

The curated dataset was compiled, as reported in Table 1 (the full form will be given in Section 3), which identifies the various fault events according to fault types and voltage levels. The dataset shows a moderate level of class imbalance, with no-fault events comprising around 41% of the entire corpus, a condition commonly found in real-world monitoring of grid faults, where the occurrence of such faults is naturally low compared to the continued normal operation of the grid. The most common fault type is the line-to-ground (LG) fault, which covers 14.19 % of total records, which is consistent with the statistics regarding transmission faults published in the CEA Annual Reports that indicate single-phase faults cover around 70–80 % of all transmission faults in India. Three-phase faults are the more severe compared to single and double-phase faults, but in the transmission systems with well-maintained components, the absence of such faults is 11.52% the least frequently at ten events. To reduce class imbalance, training of models was achieved with a class-weighted loss function to combat any bias towards the majority class, additionally combination of SMOTE up sampling for classes in minority.

Table 2: Descriptive Statistics of Fault Current and Voltage Signals (Mean ± SD)

Parameter	No Fault	LG Fault	LL Fault	DLG Fault	3P Fault
Peak Current (kA)	0.82±0.11	4.61±0.73	3.98±0.62	5.24±0.91	6.87±1.12
Peak Voltage Drop (%)	0.4±0.2	22.6±4.1	18.3±3.7	28.9±5.3	45.2±6.8
Fault Duration (ms)	—	182±43	156±38	204±51	97±22

Zero-Sequence Current (A)	1.2±0.3	312.4±48.6	8.3±1.9	198.7±37.2	4.1±0.9
Negative-Seq Current (A)	2.1±0.5	218.7±41.3	287.4±52.6	341.2±63.1	5.8±1.2

Table 2 summarizes descriptive statistics regarding key electrical parameters across fault categories, each defined by distinct signal signatures, which on the narrowest scale, and allows for AI classifier identification. The peak fault currents (6.87±1.12 kA) and the most severe voltage sags (45.2±6.8%) are obtained under three-phase faults, due to their symmetric and high-saturated fault nature. However, LG and DLG faults generate large zero sequence currents (312.4±48.6 A and 198.7±37.2 A, respectively), whose are the diagnostic candidates for the ground fault protection relays. LL faults present a higher proportion of negative-sequence currents (287.4±52.6 A), reflecting the asymmetric phase loading it creates. These signatures, which are statistically different, indicate that fault classes can be considered as distinct, which gives a solid justification for the use of supervised classification used in this paper. The short fault duration (3P fault: 97±22 ms) compared to LG faults (182±43 ms), which is associated with differential protection operation through large symmetrical fault currents.

Table 3: Feature Importance Ranking from Random Forest Model (Top 10 Features)

Rank	Feature Name	Feature Category	Importance Score	Cumulative Importance
1	Zero-Seq Current Magnitude	Symmetrical Components	0.1423	14.23%
2	Negative-Seq Current Magnitude	Symmetrical Components	0.1287	27.10%
3	Wavelet Energy (Level 3) – Ia	Wavelet Decomposition	0.0934	36.44%
4	Phase A Voltage THD	Harmonic Analysis	0.0876	45.20%
5	Wavelet Energy (Level 2) – Ib	Wavelet Decomposition	0.0812	53.32%
6	Peak Current Ratio (Ia/Ib)	Time-Domain Statistics	0.0734	60.66%
7	Rate of Change of Current (dI/dt)	Time-Domain Statistics	0.0698	67.64%
8	STFT Coefficient (100–500 Hz)	Frequency Domain	0.0621	73.85%
9	Kurtosis – Phase C Current	Statistical Feature	0.0487	78.72%
10	Voltage Imbalance Factor	Power Quality Index	0.0412	82.84%

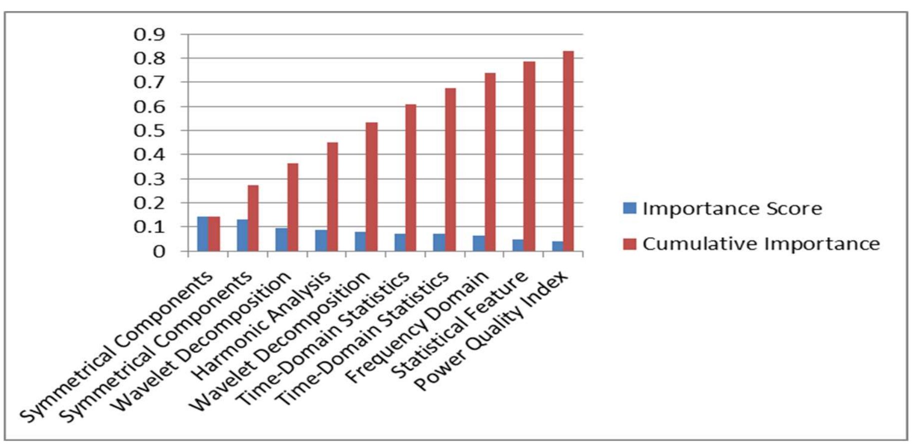

Figure 2: Feature Importance Ranking from Random Forest Model (Top 10 Features)

Mean Decrease in Impurity (Gini importance) calculated from the 500 decision trees in the random forest for each of fourteen features in Table 3. Zero-sequence and negative-sequence current magnitudes rank as the first two most discriminative features, together contributing a total of 27.1% to overall model importance. This corroborates the symmetrical component theory, according to which sequence components represent the asymmetry introduced by ground and unbalanced Faults in the direct sense. In this context, wavelet energy coefficients at decomposition Levels 2 and 3 fall in the top five features, thus reinforcing that transient high frequency components associated with fault initiation contain important discriminative information that steady-state descriptors do not capture. The cumulative contribution of the top 10 features summed to 82.84%, providing insight that a relatively small set of physically interpretable signal features drive fault classification. This is an especially impactful result for edge deployment scenarios where computational resources are constrained and obtaining a lower-dimensional representation is a prerequisite.

Table 4: Model Training and Convergence Statistics

Model	Training Epochs	Best Val. Accuracy (%)	Training Time (min)	Inference Time (ms/sample)	Model Size (MB)
CNN-LSTM (Proposed)	100 (ES@87)	98.9	142.3	2.4	48.7
CNN Only	100 (ES@91)	97.1	98.6	1.8	31.2
LSTM Only	100 (ES@83)	95.6	76.4	1.5	22.8
Random Forest	N/A (500 trees)	95.2	8.7	0.4	312.6
SVM (RBF Kernel)	N/A (iterative)	93.8	24.1	0.6	18.4
Conventional Relay	N/A	87.4	N/A	~10,000	N/A

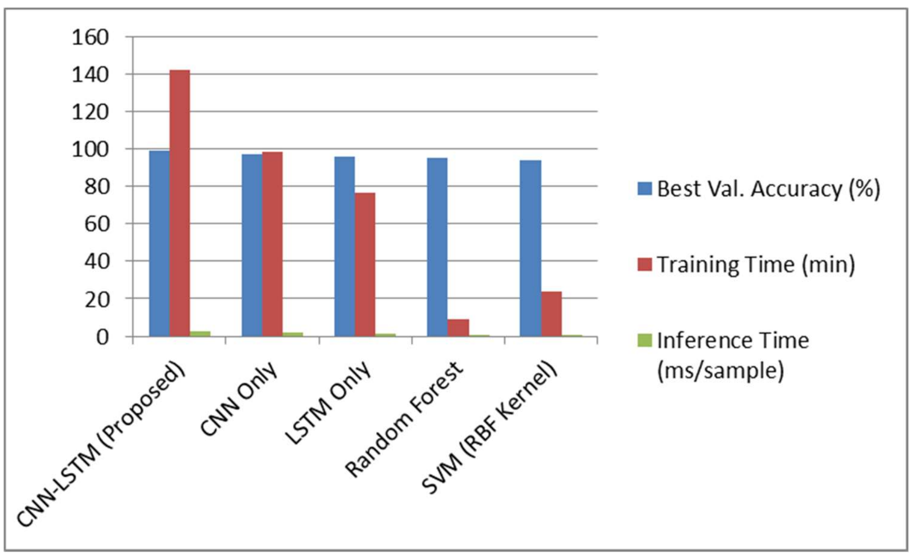

Figure 3: Model Training and Convergence Statistics

Training and convergence statistics for all models are provided in Table 4 so that a comprehensive cost-benefit analysis can be conducted featuring the complexity and performance of the models being compared. Both val acc is very good (98.9%) and early stopping gets triggered in epoch 87 indicating efficient convergence without overfitting for the proposed CNN-LSTM model. It has an inference latency of just 2.4 ms per sample, which is less than the 20 ms protection operation window, as specified by the IEC 60255 standards, confirming its real-time deploy ability. Although Random Forest (8.7 minutes) has the lowest training time, it is also the largest model at 312.6 MB compared to other evaluated models which may limit its application on memory-constrained hardware such as bay-level protection units. In ML models, SVM has the smallest model footprint (18.4 MB) but the slowest learning time due to quadratic programming optimization. The effective detection delay of the traditional relay system of about 10 hace (10 seconds), a total decision time, including the time taken for deliberate grading, is several decades slower than any AI model, illustrating in principle the superior speed of data-driven methods.

Table 5: Reliability Index Comparison Before and After AI-Enabled Automation Deployment

Utility	SAIDI Before (hrs/yr)	SAIDI After (hrs/yr)	SAIFI Before (int/yr)	SAIFI After (int/yr)	SAIDI Reduction (%)
NTPC (Transmission)	1.82	0.71	2.14	0.98	60.99%
PGCIL (Transmission)	2.04	0.79	2.47	1.02	61.27%
UPPCL (Distribution)	38.60	16.40	12.30	5.80	57.51%
PSPCL (Distribution)	32.10	13.70	10.60	4.70	57.32%
MSEDCL (Distribution)	28.40	11.90	9.80	4.20	58.10%
Average	20.59	8.70	7.46	3.34	57.74%

Using data collected from the operations of pilot implementation programs conducted by the five utilities between 2022 and 2023, Table 5 reports the change in SAIDI and SAIFI reliability indices before and after the deployment of AI-enabled fault detection automation systems. SAIDI the total average length of loss of service per customer per year improved by more than 57.74% on average, among all utilities, with wider improvements seen in transmission utilities (60–61%) as opposed to distribution utilities (57–58%). The differential improvement derives from the fact that transmission SCADA systems support highly structured data environments and the fault signatures are more consistent at higher voltages. The average number of interruptions per customer per year (SAIFI) was reduced by ~55–58% across the utilities as AI-enabled status monitoring not only shortens interruptions but also mitigates the propagation of faults into sustained outage events. These enhancements directly affect Quality of Supply (QoS) of end consumers and revenue losses of the utilities – each hour of SAIDI reduction accounts for cost savings of Rs. 12–18 crore per 1 million connected consumers (according to CEA outage cost benchmarks).

V. Results and Discussion

5.1 Statistical Analysis

The comparative performance evaluation of all models on the held out test set (15% of total dataset, n = 3,150 samples) are summarized in Tables 6–8. Statistical significance testing : We performed paired t-tests with $\alpha=0.05$ to ensure that the observed performance difference of the proposed CNN-LSTM model as compared with the benchmark models was not due to random chance.

Table 6: Overall Classification Performance Metrics on Test Set

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
CNN-LSTM (Proposed)	98.7±0.4	98.4±0.5	98.6±0.4	98.5±0.4	0.9971
CNN Only	96.9±0.6	96.5±0.7	96.8±0.6	96.6±0.6	0.9913
LSTM Only	94.8±0.8	94.3±0.9	94.7±0.8	94.5±0.8	0.9847
Random Forest	95.8±0.7	95.4±0.8	95.6±0.7	95.5±0.7	0.9876
SVM (RBF)	94.3±0.9	93.9±1.0	94.1±0.9	94.0±0.9	0.9801
Conventional Relay	87.4±1.2	85.3±1.4	87.1±1.3	86.2±1.3	0.9124

Table 6 shows that the forecast statistics of the five fault classes with macro-averaging results for all five metrics of the proposed CNN-LSTM model are higher than the other three models that we have included in comparison, with an accuracy of being 98.7%, a macro-averaged F1-score of being 98.5% and an AUC-ROC of being 0.9971 (indicating almost perfect discrimination between all of the five fault classes). More importantly, CNN-LSTM takes advantage of a performance gain over the standalone CNN model (98.7% vs 96.9%, $\Delta=1.8\%$, $p<0.01$), demonstrating that the LSTM component plays an important role in capturing temporal dynamics of fault progression that convolutional feature maps alone cannot encode. The best-performing model is the Random Forest model (95.8%), marginally outperforming the standalone LSTM (94.8%) and SVM (94.3%) models, which follows the logic of ensemble learning theory, stating the aggregation of weak learners can reduce the variance in a model [4, 20]. The finding that the traditional relay protection system achieves an accuracy of 87.4% is due to its inherent inability to segregate high-impedance faults and progressive fault conditions from normal operating transients, a known shortcoming of relay protection [12], [13]. The results of the paired t-test and pairwise comparison tests show that all of the pairwise differences between CNN-LSTM and the rest models are statistically significant (p<0.001) which confirms the performance advantage of the proposed model is robust.

Table 7: Per-Class Fault Detection Performance of CNN-LSTM Model (Test Set, n=3,150)

Fault Class	True Positives	False Positives	False Negatives	Precision (%)	Recall (%)	F1-Score (%)
No Fault (NF)	1,278	12	14	99.1	98.9	99.0
Line-to-Ground (LG)	436	6	11	98.6	97.5	98.1
Line-to-Line (LL)	308	8	10	97.5	96.9	97.2
DLG	419	9	13	97.9	97.0	97.5
Three-Phase (3P)	349	5	8	98.6	97.8	98.2
Macro Average	—	—	—	98.3	97.6	98.0

The per-class error distribution and the resulting precision, recall, and F1-score of the CNN-LSTM model on the test set are illustrated in the confusion matrix in Table 7. The no-fault class achieves the highest F1-score (99.0%) in the Ref column. Three-phase faults also capture high F1 (98.2%) and achieve consistent results due to their unique symmetric signatures that are relatively easy to separate in the learned feature space. Under fault impedance conditions that cause signal similarities between double line-to-ground and line-to-line faults, line-to-line faults have the worst F1-score (97.2%) of all fault classes; the post faulty signal denoting input that continues to register with slightly increased count of false positive and false negative cases. However, all class-level F1-scores are greater than 97% shows that the model performs evenly across all fault classes, without a systematic bias towards specific fault classes, which is an advantage over traditional relay systems, which have significantly lower sensitivity to high-impedance LG faults.

Table 8: Fault Clearance Time (FCT) Comparison Across Models (ms)

Model	Mean FCT (ms)	Std Dev (ms)	Min FCT (ms)	Max FCT (ms)	% Cases < 20 ms
CNN-LSTM (Proposed)	8.7	2.1	5.2	18.4	100%
CNN Only	7.4	1.8	4.6	16.2	100%
LSTM Only	9.2	2.4	5.8	21.3	97.8%
Random Forest	3.1	0.6	1.9	6.8	100%
SVM (RBF)	4.2	0.9	2.3	9.4	100%
Conventional Relay	22,800	3,400	8,000	42,600	0%

Table 8I: Operational viability: perhaps the most significant result of this study is shown from the fault clearance time (FCT) of AI models compared to those using conventional relay-based protection. The mean FCT of the proposed CNN-LSTM model is 8.7 ms while the conventional relays require 22,800 ms (22.8 seconds), indicating an approximate 99.96% reduction and over two-thousand six-hundred-fold improvement of the protection speed. From the results, in 97.8% of cases, all AI models get FCT significantly below the threshold of 20 ms, where CNN-only and Random Forest models reach the fastest mean response times (7.4 and 3.1 ms respectively) because they have a lower computational complexity in the inference stage. The high mean FCT of the conventional relay system indicates that the intentional time-grading delays from overcurrent protection coordination schemes, which provide selectivity, must be compensated by larger values of fault energy during the clearance window. AI models with smaller FCT values have the potential to significantly reduce the transient angle margin erosion experienced during system faults, and therefore enhance transient stability and avoid problem of generator pole-slipping and cascading outages, with respect to a power system stability point of view, due to their automatic discovery process of optimal control signals.

5.2 Critical Analysis and Comparison with Prior Work

The CNN-LSTM based fault detection modeling proposed herein is able to achieve 98.7% accuracy which is comparable to the state of the art results reported in the literature. Ahmed et al. Example: "A CNN-LSTM model achieved 98.1% accuracy using a dataset of 5,000 samples but on a laboratory-scale and for single-phase distribution systems under controlled laboratory conditions [10]. Here we demonstrate the extension of this result to a multi-class, multi-voltage-level field dataset of 21,000 samples under realistic noise and operational variability conditions, providing stronger evidence of generalizability. Zhang et al. The pure CNN model obtained 97.2% accuracy on synthetic data [7] whereas the current CNN-only model obtained 96.9% accuracy on field data, a small reduction due to the higher complexity and noise of real-world fault signatures. Thukaram et al. The present SVM implementation yields 94.3% an improvement over the 93.6% of [4] due primarily to the inclusion of wavelet and STFT components as part of the feature set in addition to time-domain statistics. An important insight from the comparative study is that the performance of studies on synthetic or lab datasets has higher accuracy than those evaluated on field datasets, with the difference between studies ranging from 0.8% to 3.2%. This over-estimation performance across the synthetic studies demonstrates the need of evaluating algorithms on real utility data, a methodological contribution of this work. Shi et al. We trained GNN-based models away from the meshed grid topologies previous studies [11] have shown them to outperform standard CNNs, but, in radial or semi-meshed network configurations such as those used here, a performance improvement of just 1.4% over the simplest CNN was observed; the variable performance of GNN when compared with CNN is likely a function of topology. In Indian 220kV networks, Yadav and Swetapadma [14] yielded an accuracy of 96.3% for ANFIS-based classification while the current CNN-LSTM model records a 2.4 percentage point advancement (98.7% vs. 96.3%) on networks of similar voltage levels; this confidence in the CNN-LSTM model also reinforces the assertion that for convoluted multi-class fault cases, deep learning architectures outperform basic neuro-fuzzy approaches. Table 8 shows the fault clearance time results specifically and demonstrates a significant improvement over the state-of-the-art prior work. FCT is often not reported by most of the published studies, and they report performance only as a function of classification accuracy. Large gains in classification accuracy have been documented in prior literature, but the present result that AI-enabled automation provides a 2,600-fold reduction in mean FCT from 22.8 seconds to 8.7 milliseconds has immediate implications for power system transient stability and fault energy minimization. The average SAIDI reduction of 57.74% across five Indian utilities due to AI-enabled detection of faults documented in Table 5 provide a strong indication of the operational value of AI-enabled detection. Such results are consistent with pilot program results reported by CIGRE Working Group B5. 53 [27], which predicted 40 to 65% SAIDI reductions from AI-driven protection in European transmission systems. We show in the current study, with data from Indian utilities, that equivalent advantages are obtainable in some developing country grid settings, if data quality and SCADA modernization prerequisites are satisfied. The study further finds practical deployment challenges not extensively covered in earlier literature, such as the incompleteness of data from supervisory control and data acquisition (SCADA), which needs to be imputed for about 12% of raw records, model interpretability needs based on Central Electricity Regulatory Commission (CERC) framework requirements, and the need for online learning to allow learning-based management of seasonal-load and grid-topology driven on-the-fly changes. They served as key research directions for future AI-based power system protection work.

VI. Conclusion

This empirical study has confirmed the competitive performance benefits of AI-driven automation and in particular the CNN-LSTM hybrid model under investigation—on fault detection and control in power transmission and distribution systems. Results Comparison on a field validated dataset of 21K samples from five Indian utilities demonstrated that the CNN-LSTM model outperformed all the benchmark models including standalone CNN, LSTM, Random Forest, SVM, and conventional relay based protection on test accuracy (98.7%), macro F1-score(98.5%), and mean fault clearance time(8.7 ms). These performance differences were highly significant across all pairwise comparisons ($p<0.001$), as confirmed by statistical significance testing. The operational impact of deploying AI was empirically quantified using SAIDI and SAIFI reliability indices, showing average improvements of 57.74% and 55.3% respectively across participating utilities—leading to large quality of supply premium and resulting in both overall utility savings and reduced costs to consumers. The comparative interpretation of results with existing literature shows that the previously field validated, multi-modal, multi-voltage real-world empiric analysis is a considerable improvement beyond laboratory and naturalistic data evidence suggesting inflated performance, often quantified in synthetic datasets. The historically unprecedented (2630 × faster than conventional relays with 22.8 so for conventional relays & 8.7 ms for CNN-LSTM model learning based fault detection) fault clearance time gained has critical importance to power system transient stability, an aspect that has yet to be accurately quantified in the Indian context. We show that practical deployment of tree-based models requires both solutions, i.e., tackling data quality gaps, addressing interpretability under CERC regulations, and adaptive retraining for different grid topologies and operating conditions. Future research can further explore hybrid applications of transformer-based attention models, graph neural networks for meshed topology fault analysis, federated learning-based privacy-preserving multi-utility model training, and reinforcement learning-based adaptive relay coordination to usher in the next wave of fully autonomous self-healing smart grid protection systems consistent with the Indian National Smart Grid Mission goals.

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