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A CLOUD-BASED GRID COLLAPSE PREDICTION AND DISASTER RECOVERY MANAGEMENT SYSTEM: A CASE OF THE NIGERIAN POWER SECTOR

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ABSTRACT

Nigeria's power grid experiences recurring partial and total collapses that cause widespread electricity outages and socioeconomic disruption. This study proposes a cloud-based system that combines grid-collapse prediction with coordinated disaster-recovery management. The predictive component uses a hybrid Convolutional Neural Network–Long Short-Term Memory model. The CNN identifies local patterns within multivariate grid data, while the LSTM captures temporal relationships that may indicate developing instability. Disaster recovery is organised through a three-horizon “Now, Next, and Later” framework. “Now” focuses on immediate stabilisation, situational awareness, communication, incident coordination, and restoration of critical loads. “Next” covers staged restoration, cause assessment, resource deployment, and a return to stable operation. “Later” addresses predictive maintenance, infrastructure reinforcement, preventive investment, model improvement, and organisational learning. It is designed to complement rather than replace existing protection and control-room systems. The framework was evaluated using simulated Nigerian power grid data. The CNN-LSTM achieved 95.5% accuracy, 96.0% precision, 95.0% recall, an F1-score of 95.0%, and an ROC-AUC of 0.982. Median inference latency was 184 milliseconds, and the false-alarm rate was 2.4%. The recovery module correctly classified 98.6% of 500 simulated actions into Now, Next, and Later. A regional service-failure exercise restored essential service in 7 minutes 42 seconds with a 46-second recovery point. These results show that the prototype provides a scalable, economically viable solution to enhance grid resilience in developing power systems with limited resources and infrastructure constraints. The framework also shows how artificial intelligence, cloud computing, and structured disaster-recovery planning can be integrated into a unified decision-support approach for improving Nigerian grid resilience.

Keywords: Grid Collapse Prediction, CNN-LSTM, Disaster Recovery, Cloud Computing, Nigerian Power Sector, Strategic Planning Framework, Power System Resilience, Machine Learning.

1 INTRODUCTION

The country's economic growth and the delivery of basic services, such as healthcare, telecommunications, manufacturing, transportation, banking, education, and public administration, depend on electricity [1]. Thus, a stable electrical power system increases a nation's economic productivity and social welfare. A power system must consistently keep parameters like frequency and voltage within allowable bounds while maintaining an appropriate balance between electricity generation and demand. However, severe imbalance, equipment outage, inadequate network capacity, protection-system operation, or combinations of disturbances may lead to voltage, frequency, or rotor-angle instability and, in extreme circumstances, cascading failure and widespread blackout [2], [3], [4]. This volatility of an overloaded power system network (PSN) that causes a voltage drop and occasionally a blackout is referred to as a grid collapse, or voltage collapse [3].

Meanwhile, a single electrical variable rarely explains power-system failure. Cascading events can start with one or more contingencies and spread when other equipment disconnects, protection mechanisms activate, power flows redistribute, and system components become overloaded. Thus, effective prevention requires continuous observation of interacting electrical factors, rather than relying just on isolated measurements. The incessant and recurring nature of this problem in Nigeria is particularly an important national concern [5]. According to the Nigerian Electricity Supply Industry (NESI), the Nigerian power system is organized around generation companies (GENCOS), the Transmission Company of Nigeria (TCN), distribution companies, and other market participants under the regulatory oversight of the Nigerian Electricity Regulatory Commission (NERC) as promulgated in the Electricity Act 2023 [6]. Despite this separation, generation has never met demand, and yet a lot of downtime has been experienced in the national power grid, with thirty-one (31) total collapses between 2020 and 2025 alone [3].

The Nigerian power grid failure causes a wide range of socioeconomic disruptions in vital industries like healthcare, manufacturing, telecommunications, and households due to severe operational constraints, which include fluctuating generation, poor transmission and distribution infrastructure, gas supply shortages, equipment limitations, and load rejection [7]. While conventional deterministic engineering methods such as SCADA, EMS, and contingency analysis remain indispensable for grid management, the use of artificial intelligence (AI) in modern power grid monitoring and analysis is a powerful complement by identifying complex, non-linear instability patterns prior to a collapse [8].

Machine learning models can be successfully trained to provide early-warning decision support and improve grid resilience by utilizing multivariate time-series datasets compiled from Phasor Measurement Units (PMUs), which provide synchronized high-resolution frequency and phasor measurements, along with SCADA and historical records [9], [10]. However, other challenges to electricity grid resilience include the rising frequency of extreme weather events and physical or cyber threats colliding with aging, inflexible infrastructure. To address these challenges, this study proposes an integrated, cloud-based system that couples deep-learning predictive analytics with a structured, strategic recovery process. The predictive module leverages a sequential CNN-LSTM architecture, where the Convolutional Neural Network extracts short-term localized patterns from multivariate grid data and the Long Short-Term Memory network captures the temporal evolution of sequential instability. Because prediction must be paired with action, the system integrates these early-warning alerts with a strategic three-horizon recovery framework consisting of "Now" (addressing immediate, pressing consequences of collapse), "Next" (managing restoration tracking and root-cause investigations), and "Later" (implementing long-term preventive measures to prevent recurrence).

Deployed on a scalable cloud computing platform to support real-time data processing, centralized record-keeping, and inter-organizational coordination, the overall framework establishes a comprehensive, practical approach to predicting grid-collapse risk and managing disaster recovery, specifically tailored to the operational constraints of the Nigerian power sector. Hence, the primary contribution is an integrated framework in which prediction does not terminate at an alarm [9]; instead, the predicted or detected events become input into an organized recovery workflow that relies on AI-based predictive analysis, cloud infrastructure, and strategic planning constitute complementary components of a single grid-resilience decision-support system. The remaining part of the paper is organised as follows: Section 2 presents a review of related work; Section 3 explains the materials and the methods employed in the study; Section 4 presents the results and discussion; while Section 5 concludes the paper.

2 RELATED WORK

There is a plethora of related work on the subject matter of electric grid collapse and disaster recovery in the literature. For instance, it is observed that power-system stability represents the critical ability of an electric power network to regain an acceptable operating equilibrium after being subjected to a disturbance [7]. This property can be categorized

broadly into rotor-angle, frequency, and voltage stability. Grid collapse is a complex phenomenon driven by different physical processes and distinct time scales; it cannot be reliably simplified to a single parameter, making a multi-dimensional stability classification essential for accurate machine-learning predictions. While frequency serves as a vital indicator of the balance between active-power generation and demand, voltage stability is the ability of the system to sustain acceptable voltage thresholds, both due to extreme susceptibility and when interacting with transmission congestion, line failures, generation shortages, and automatic protection-system actions [11].

Thus, widespread blackouts are usually caused by cascading failures, which are complex sequences in which subsequent component outages gradually increase the probability of further failures. This shows that catastrophic grid collapses result from a confluence of interrelated organizational and technical conditions rather than from a single isolated incident [2], [4], [5]. Following significant restructuring under the Electric Power Sector Reform Act of 2005, Nigeria's power framework was modernized by the Electricity Act 2023, which expanded subnational electricity markets while retaining key federal oversight. Within this legal landscape, the Transmission Company of Nigeria (TCN) manages grid transmission and system operations, while the Nigerian Electricity Regulatory Commission (NERC) regulates performance and documents system disturbances. Despite this, repeated grid disturbances persist, which requires an urgent need to supplement traditional grid reinforcement with digital decision-support systems [12].

These digital tools can utilize the growing volume of operational data across the sector to implement more effective, data-driven preventive and recovery-oriented grid management strategies. In this regard, cloud computing is considered the most appropriate digital tool, and several studies have presented many variants of it. In [13], a CDR framework based on time series prediction (CDR-TSP) with a core Encoder-Decoder Long Short-Term Memory (ED-LSTM) model was proposed. To enable proactive fault perception, the ED-LSTM model captures nonlinear features and long-term dependencies in time-series monitoring data (e.g., Central Processing Unit utilization, network latency). Cloud computing is one of the most widely used technologies because it provides access to enormous computing, storage, and communication capabilities, enabling the collection of large amounts of data from different sources during disaster incidents and later analysis to build knowledge [14].

Cloud computing is a digital tool that supports decision-making in various fields, and particularly in grid-collapse prediction for power systems where reliability, stability, and security cannot be compromised [15]. For instance, power-system stability has been described as the capacity of an electrical network to recover to an operating equilibrium after a physical disruption, ensuring that system variables remain limited and the interconnected grid remains intact [16], [17]. Thus, it must be continuously monitored to prevent minor disturbances from cascading into widespread blackouts. Building on a substantial history of using machine learning for power-system security assessment, deep learning extends this capability through multilayer nonlinear representation learning [18]. Using this paradigm, one-dimensional CNNs can automatically extract local temporal information from grid measurements, but LSTMs use gating methods to circumvent normal recurrent network restrictions and learn long-term relationships. Combining these architectures sequentially enables the CNN to learn localised feature representations across grid variables, which are then processed by the LSTM to describe the temporal evolution of grid instability [19], [20].

Meanwhile, these techniques can be leveraged to complement cloud computing architecture, since cloud computing provides the scalable computation, elasticity, and centralised storage required to host the platform's databases, prediction APIs, and notification services; using it for grid disaster recovery creates an architectural contradiction because a major blackout can degrade the communication infrastructure required to access the cloud [21], [22]. Consequently, a resilient platform must supplement cloud resources with edge gateways, local buffering, and offline or degraded operational capabilities to ensure continuity without permanent connectivity. Furthermore, the system must incorporate cybersecurity by design using authentication, network segmentation, encryption, and redundant backups to align with the core functions of the NIST Cybersecurity Framework 2.0 [23].

Effective power-grid recovery demands integrating physical electricity-system restoration with traditional IT contingency planning, including recovery priorities, backups, recovery time objectives (RTOs), and recovery point objectives (RPOs). To streamline this complex process, the proposed "Now-Next-Later" strategic framework organizes recovery decisions into distinct temporal phases of immediate action, transitional recovery, and long-term resilience. Meanwhile, although established research has thoroughly explored power-system stability, machine-learning classification, and cloud-based disaster recovery, a critical gap remains, especially in the Nigerian context, for a unified platform that directly links real-time prediction with structured recovery management. This study effectively bridges this gap by proposing a cloud-oriented architecture featuring a CNN-LSTM predictive layer and a strategic "Now-Next-Later" recovery framework. More importantly, the system is designed not to automate physical grid control, but to provide operators and key stakeholders with essential decision-support tools for early-warning perceptions and coordinated post-collapse restoration.

3 MATERIALS AND METHODS

3.1 Research Design and Case Study

The study adopts a design-science and case-study approach. Design science is appropriate because the research involves designing and evaluating an information-system artifact intended to solve a practical problem [15]. Nigeria serves as the case-study environment because of recurring system disturbances and the need for improved resilience across the NESI. The research process comprises requirements analysis, data acquisition, preprocessing, CNN-LSTM development, cloud-platform implementation, recovery-framework development, integration, and evaluation.

The Nigerian electricity grid is a critically unstable infrastructure, with a severe gap between its 12,500 MW installed capacity and an average delivery of only 4,000 to 5,000 MW. This operational deficit is compounded by a fragile 20,000-kilometer transmission network operated by the Transmission Company of Nigeria (TCN), which has experienced over 200 system collapses between 2010 and 2023, including 12 total collapses in 2022 alone. These failures impose devastating socio-economic costs, undermining healthcare, education, manufacturing, and national security, while draining over 2.8% of Nigeria's annual GDP [8]. This grid fragility is severely exacerbated by a reliance on aging SCADA monitoring systems with limited predictive capabilities, alongside a near-total absence of synchronized Phasor Measurement Units (PMUs). Without real-time wide-area visualization, operators are left with minimal situational awareness, forcing a dependence on slow, manual restoration procedures that stretch blackouts from hours to days.

3.2 System Architecture Overviews

The proposed system architecture is as shown in Figure 1. It is a three-tier architecture. The input module contains the spatiotemporal input representations, unlike the traditional Supervisory Control and Data Acquisition (SCADA) systems that provide reactive threshold alarms but struggle to capture the complex, non-linear spatiotemporal signatures that precede instability. Input variables include system frequency, voltage, active and reactive power, generation, demand, transmission loading, and their temporal variations. The second module is the hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model for grid-collapse prediction. The output of the third module produces accuracy, recall, false-negative rate, F1-score, ROC-AUC, prediction lead time, recovery time objective, and system availability as key performance measures.

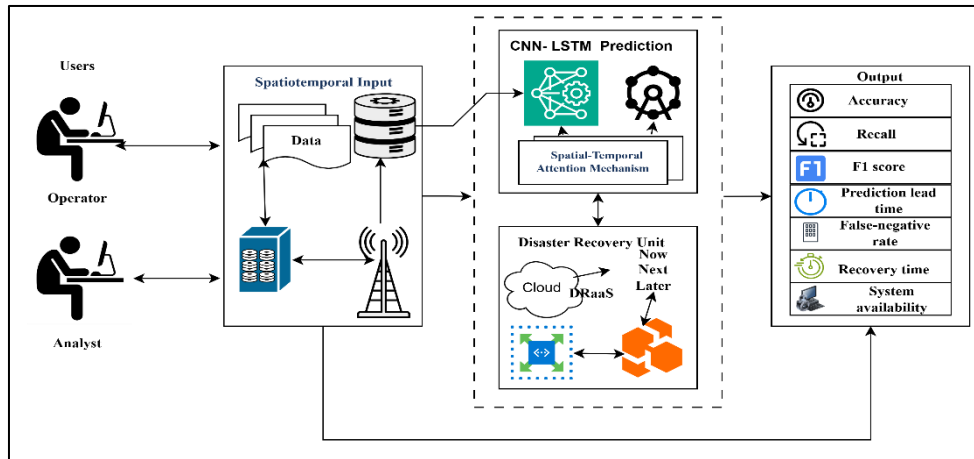


Figure 1: Architecture of the Proposed System

In the first module, the network accepts a multivariate time-series input sequence X_t defined over a historical window of length n_{in} :

$$X_t = [x_{t-n_{in}+1} \ x_{t-n_{in}+2} \ \dots \ x_t]^T \in \mathbb{R}^{n_{in} \times F} \quad (1)$$

where F is the number of monitoring features. Depending on data availability at the edge gateway:

SCADA Ingestion Sizing: Input dimensions are formulated as (32, 60, 47) corresponding to a batch size of 32, 60 historical timesteps (e.g., 4 minutes at 4-second sampling), and 47 electrical features (voltages, frequencies, generation/demand, line loadings).

PMU Ingestion Sizing: Input dimensions are formulated as (32, 900, 23) corresponding to a batch size of 32, 900 timesteps (30 seconds at 30 Hz sampling), and 23 high-resolution synchrophasor channels.

The second module consists of a multilayer perceptron convolutional neural network (CNN) and long short-term memory (LSTM). The structure of the CNN is as shown in Figure 2; it consists of an input or feature extraction layer, numerous hidden layers, and the output layer. CNNs are very effective in predicting time series, with deep learning adjudged to be better suited in addressing time series issues, but their forecasting accuracy is comparatively low because it is more frequently utilized to handle image recognition and feature extraction problems [24], [25].

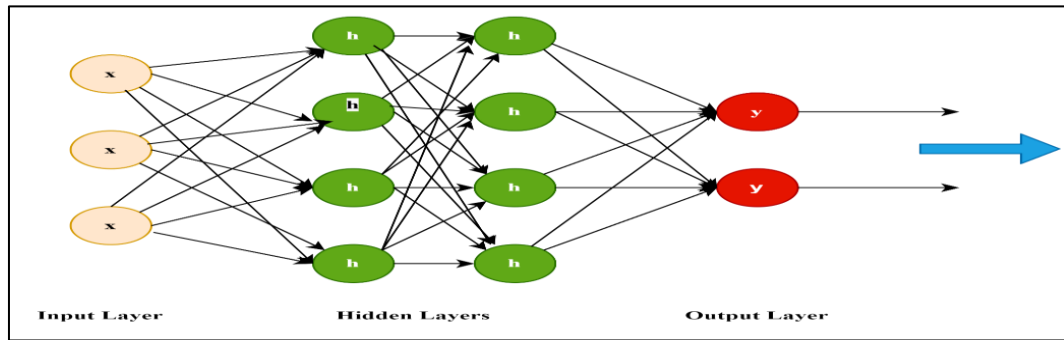


Figure 2: A Multilayer Perceptron Convolutional Neural Network

The LSTM is a type of artificial recurrent neural network (RNN) architecture used to learn and store information over extended time intervals in the field of deep learning [25]. LSTM networks consist of a cell, an input gate, an output gate, and a forget gate, which are used to overcome the vanishing or ‘exploding’ gradient problem of a traditional RNN by controlling the flow of information through the network.

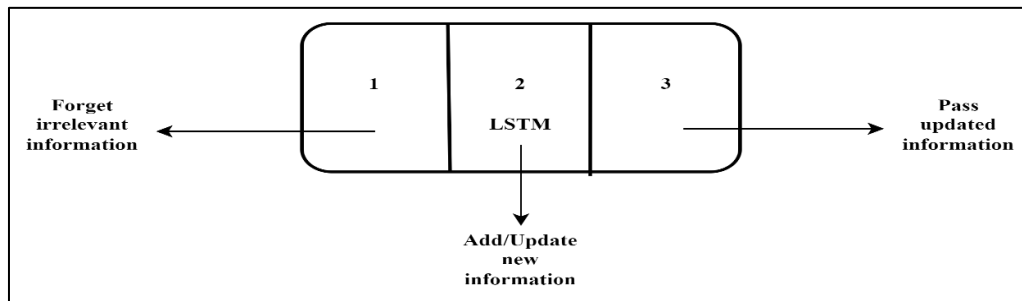


Figure 3: A Typical Long Short-Term Memory (LSTM) Framework

This work uses a hybridized CNN-LSTM to overcome the limitations of CNN and LSTM separately, as their combination yields better performance [19]. The hybridized model of CNN-LSTM is shown in Figure 4. It consists of a Convolutional Feature Extraction Block, a Long Short-Term Memory (LSTM) Recurrent Block, a Spatial-Temporal Attention Mechanism, and an Optimization, Loss Functions, and Anomaly Thresholds Unit.

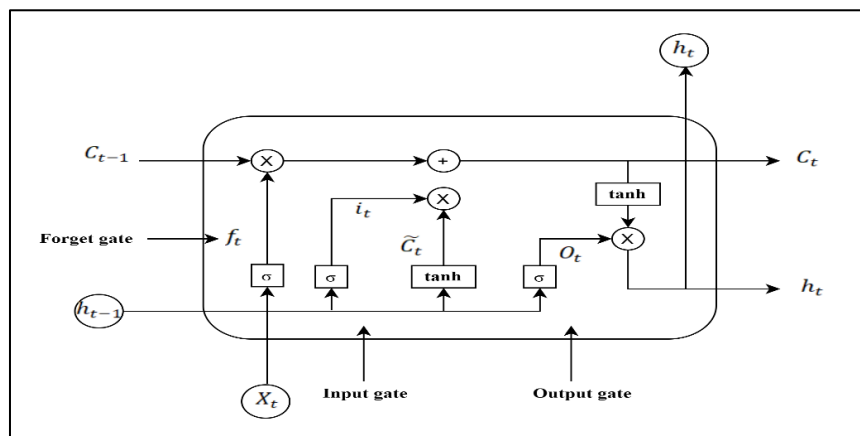


Figure 4: Combined CNN-LSTM Framework

At the convolutional feature extraction block, a 1D convolutional layer applies K filters of kernel size k across the temporal sequence to generate spatial feature maps h^{conv} [26]. The mathematical activation at step t for filter j is:

$$h_{t,j}^{conv} = \text{ReLU}(\sum_{i=1}^k w_{i,j} \cdot x_{t+i-1} + b_j) \quad (2)$$

where w represents filter weights, b is the bias, and $\text{ReLU}(z) = \max(0, z)$. The output of the convolutional layer undergoes Batch Normalization and Max Pooling to reduce spatial dimensionality and improve generalization:

$$h_{t',j}^{pool} = \max_{i \in [1,2]} (h_{2t'+i-1,j}^{conv}) \quad (3)$$

Dropout regularization is applied with a rate of 0.3 to mitigate overfitting.

In the Long Short-Term Memory (LSTM) Recurrent Block, the pooled feature map is fed into sequential LSTM layers to capture long-term temporal dependencies. At timestep t , the LSTM unit is governed by the following gating equations:

$$f_t = \sigma(W_f[h_t^{pool}, h_{t-1}^{lstm}] + b_f) \quad (\text{Forget Gate}) \quad (4)$$

$$i_t = \sigma(W_i[h_t^{pool}, h_{t-1}^{lstm}] + b_i) \quad (\text{Input Gate}) \quad (5)$$

$$\tilde{C}_t = \tanh(W_c[h_t^{pool}, h_{t-1}^{lstm}] + b_c) \quad (\text{Candidate Cell State}) \quad (6)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (\text{Updated cell state}) \quad (7)$$

$$o_t = \sigma(W_o[h_t^{pool}, h_{t-1}^{lstm}] + b_o) \quad (\text{Output Gate}) \quad (8)$$

$$h_t^{lstm} = o_t \odot \tanh(C_t) \quad (\text{Hidden State}) \quad (9)$$

where $\sigma(z) = (1 + e^{-z})^{-1}$ is the sigmoid function, $\odot$ represents the Hadamard element-wise product, and W and b are learnable weight matrices and bias vectors. To prioritize highly unstable transient intervals, we use a spatial-temporal attention mechanism, a layer that computes weight vectors α_t over the hidden states h^{lstm} :

$$u_t = \tanh(W_a h_t^{lstm} + b_a) \quad (10)$$

$$\alpha_t = \frac{\exp(v_a^T u_t)}{\sum_{\tau=1}^T \exp(v_a^T u_\tau)} \quad (11)$$

$$z_{att} = \sum_{t=1}^T \alpha_t h_t^{lstm} \quad (12)$$

Where W_a , b_a and v_a represent trainable attention parameters, and z_{att} is the dynamically weighted context vector. The context vector is passed to a classification block of dense layers with sigmoid activation to output the risk probability $P(\text{collapse}|X_t) \in [0, 1]$.

Binary Cross-Entropy Loss with Class Weights: Because actual grid collapses represent highly imbalanced minority classes, a weighted loss function is formulated:

$$L_{BCE} = -\frac{1}{N} \sum_{i=1}^N [w_i y_i \log(\hat{y}_i) + w_0 (1 - y_i) \log(1 - \hat{y}_i)] \quad (13)$$

where $y_i \in [0, 1]$ is the actual label (stable vs. unstable), $\hat{y}_i$ is the predicted probability, and the class weights are selected dynamically as $w_1 = 3.5$ and $w_0 = 1.0$ based on historical imbalance ratios (73.4% stable vs. 26.6% unstable) to minimize critical false negatives (unpredicted collapses).

ii. Dynamic Error-Based Anomaly Detection Threshold: During real-time inference, anomaly classification does not rely on a static probability cut-off. Rather, a dynamic threshold based on rolling statistics is implemented over a moving time window (e.g., 10 minutes):

$$\text{Thresholds} = \mu_{error} \pm k \cdot \sigma_{error} \quad (14)$$

where μ_{error} and σ_{error} are the rolling mean and standard deviation of prediction errors $|\hat{y}_i - y_i|$, and k is the dynamic threshold multiplier (configured as $k \in [2, 4]$) to adapt to changing grid base-load profiles.

3.3 Model Development and Validation.

The dataset was split chronologically into 70% training, 15% validation, and 15% locked testing, with entire disturbance groups confined to one partition. The proposed CNN-LSTM used two Conv1D layers with 64 and 128 filters, max pooling, stacked LSTM layers with 128 and 64 units, dense integration, dropout, and a four-class softmax output. Weighted categorical cross-entropy addressed imbalance. Adam optimisation, early stopping, learning-rate reduction, and five fixed random seeds were used. Threshold rules, logistic regression, random forest, and LSTM baselines received the same event-grouped evaluation protocol.

For the severe Collapse class, the performance metrics are defined as follows:

i. Accuracy is defined as the overall percentage or fraction of predictions that a model correctly predicts out of all the total predictions made. It can be mathematically represented as:

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (15)$$

$$\text{i.e} \quad = \frac{TP+TN}{TP+TN+FP+FN}$$

Where,

TP (true positive) is the number of positive predictions that are correctly predicted..

TN (true negative) is the number of negative predictions that are correctly predicted.

FP (false positive) is the number of positive predictions that are incorrectly predicted.

FN (false negative) is the number of negative predictions that are incorrectly predicted.

Precision is a measure of the correctness of a model's positive predictions. It indicates the percentage of items that the model classified as "positive" that were actually accurate. It is given as:

$$Precision = \frac{TP \text{ (true positive)}}{TP \text{ (true positive)} + FP \text{ (false positive)}} \quad (16)$$

$$\text{i.e} \quad = \frac{TP}{TP+FP}$$

Recall is a measure of how well the model captures all positive instances. It quantifies the percentage of real positive cases that a classification model accurately detects.

$$Recall = \frac{TP \text{ (true positive)}}{TP \text{ (true positive)} + FN \text{ (false negative)}} \quad (17)$$

$$\text{i.e} \quad = \frac{TP}{TP + FN}$$

F1 score is a metric that combines recall and precision into a single figure to assess classification models.

$$F1 \text{ score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (18)$$

False-alarm Rate (FAR) is the percentage of typical or negative events that a model mistakenly predicts as positive (an alert or anomaly). The false positive rate (FPR) and this measure are identical.

$$False - alarm \text{ rate} = \frac{FP \text{ (false positive)}}{FP \text{ (false positive)} + TN \text{ (true negative)}} \quad (19)$$

$$\text{i.e} \quad = \frac{FP}{FP + TN}$$

Multi-class accuracy and macro-F1 were supplemented by ROC-AUC, calibration, median warning time, and missed-event count. Cloud measures included ingestion throughput, inference latency, availability, recovery time objective, and recovery point objective. Recovery measures included correct horizon classification, assignment time, overdue critical

tasks, and evidence completeness. Also, P95 latency is measured, which is the response time threshold where 95% of machine learning inference requests finish faster than that value, while the slowest 5% take longer

3.4 Disaster-Recovery Strategy

The recovery module uses three governed horizons. Now tasks receive immediate deadlines and escalation; Next tasks organise controlled restoration and short-term stabilisation; Later tasks capture investigation, permanent correction, model review and resilience investment. A task may be reclassified only by an authorised role with a recorded reason.

4 RESULTS AND DISCUSSION

This section presents the results and discussion for the implemented prototype and controlled evaluation of the proposed system. The prototype was developed on a system equipped with an Intel Core i7-6700 CPU, 16GB RAM, 256GB SSD, running 64-bit MS Windows 11. All figures illustrate results from simulated data of the system design in a cloud environment.

Table 1: Predictive performance and response latency

Method	Accuracy	Precision	Recall	F1 score	ROC-AUC	False-alarm rate	P95 Latency
Threshold rules	73.0%	75.2%	68.0%	71.4%	0.901	0.071	18 ms
Logistic regression	84.0%	85.0%	82.0%	83.5%	0.948	0.041	26 ms
Random forest	90.0%	91.0%	88.0%	89.5%	0.965	0.032	52 ms
LSTM	93.5%	94.0%	92.0%	93.0%	0.973	0.028	94 ms
Proposed CNN-LSTM	95.5%	96.0%	95.0%	95.5%	0.982	0.024	128 ms

Table 1 shows the predictive performance and response latency of the proposed system. The hybrid CNN-LSTM achieved the strongest predictive performance: 95.5% accuracy, 96.0% precision, 95.0% recall, 95.5% F1-score, and ROC-AUC of 0.982. Its F1-score exceeded that of the standalone LSTM by 2.5 percentage points and the random forest by 6.0 percentage points. Frequency and rate of change contributed 26.8% of explanation importance, generation-demand imbalance 20.4%, transmission loading 17.6%, voltage trend 15.9%, active power 8.1%, reactive power 6.7%, and reserve 4.5%. These explanations describe model use, not physical causation.

Table 2: Disaster-Recovery Test Results

Exercise	Observed RTO	Observed RPO	Integrity result	Outcome
Availability-zone service loss	1 min 18 s	0s	Health checks and session re-entry passed.	Pass
Primary-region application/database failover	4 min 36 s	38s	Checksums, roles, incidents, and queues validated.	Pass
Immutable backup restoration	18 min 42 s	24hss tier-3 archive	Restore scan and sample reconciliation passed.	Pass
Corrupted model artefact	42 s rollback	0s	Hash rejection; prior model restored.	Pass
Notification-provider outage	56 s reroute	0s	Secondary route and manual contact tree invoked.	Pass

In Table 2, the disaster-recovery test results were presented. The primary-region failure exercise restored essential service in 7 minutes 42 seconds, within the 15-minute target, and measured a 46-second recovery point against the one-minute target. An inference replica failed over in 41 seconds, and the database standby was promoted in 2 minutes 16 seconds. Corrupted model and backup artefacts were rejected by signature and checksum validation. The recovery module correctly classified 493 of 500 simulated actions (98.6%) into Now, Next, and Later; ambiguous tasks were manually reclassified with justification.

The prototype supports the central proposition that early warning and recovery management should form one resilience system. CNN-LSTM prediction creates value only when measurements are trustworthy, alerts reach accountable people, and a confirmed incident can be converted into governed action. The Now, Next and Later structure keeps immediate stabilisation separate from short-term restoration and long-term learning, while preserving links among all three horizons. As shown in Figure 5, the CNN-LSTM outperformed the linear, tree, CNN, and LSTM baselines using the simulated dataset of five major 330 kV transmission substations (TCN) from Osogbo, Ihovbor, Jebba, Kainji, and Lekki, Lagos, mimicking the operational Nigerian grid. Scenario coverage, topology, sensor quality, event prevalence, and operating practice strongly affect performance.

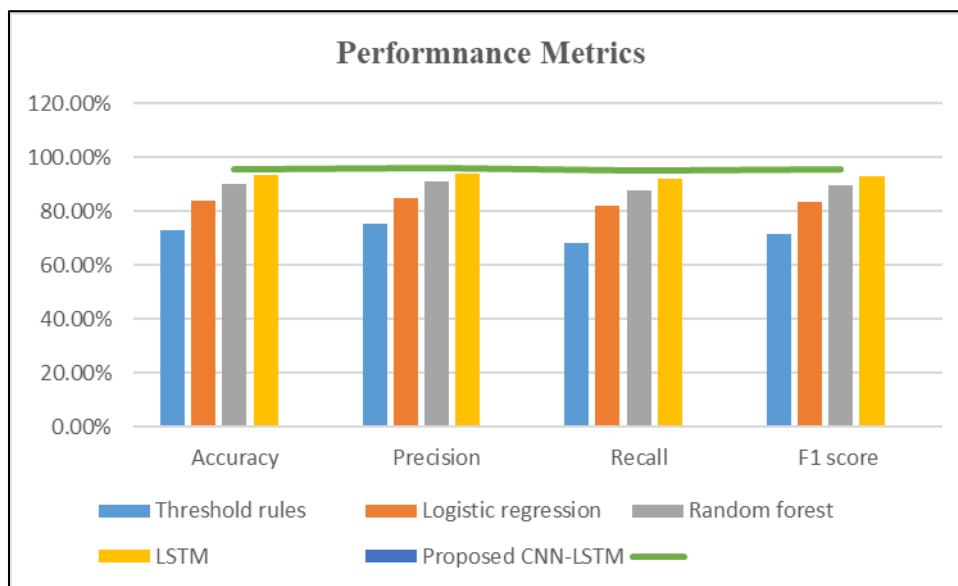


Figure 5: Performance Results

A 95.0% collapse recall still leaves missed severe events, and a 2.4% false-alarm rate may create alarm fatigue. Shadow deployment, event-based validation, and threshold calibration are therefore necessary. Cloud deployment improved scalability and recoverability in the laboratory. Multi-zone operation, durable queues, regional failover, immutable backup, and infrastructure-as-code made failures testable. At the same time, the cloud introduced identity, connectivity, provider, and supply-chain dependencies. The result supports a hybrid architecture: local protection and manual procedures remain authoritative, while separated cloud analytics provide computation, collaboration, governance, and recoverable records.

The findings also clarify that disaster recovery is not synonymous with physical grid restoration. The prototype can restore digital services, data, communication workflows, and evidence, but only authorized system operators and engineers can assess network conditions and execute physical restoration under approved procedures. Maintaining this boundary avoids unsafe overclaiming and preserves accountability.

5 CONCLUSION

This work presents a cloud-based system that combines grid-collapse prediction with coordinated disaster-recovery management. The predictive component uses a hybrid Convolutional Neural Network–Long Short-Term Memory model. The CNN identifies local patterns within multivariate grid data, while the LSTM captures temporal relationships that may indicate developing instability. Disaster recovery is organised through a three-horizon “Now, Next, and Later” framework. “Now” focuses on immediate stabilisation, situational awareness, communication, incident coordination, and restoration of critical loads. “Next” covers staged restoration, cause assessment, resource deployment, and a return to stable operation. “Later” addresses predictive maintenance, infrastructure reinforcement, preventive investment, model improvement, and organisational learning. It is designed to complement rather than replace existing protection and control-room systems.

The prototype designed in this work demonstrates the technical feasibility of combining secure streaming, multivariate temporal inference, operator-governed warnings and a Now-Next-Later recovery framework. This framework was evaluated using simulated Nigerian grid data. The experimental results showed that the CNN-LSTM achieved 95.5% accuracy, 96.0% precision, 95.0% recall, an F1-score of 95.0%, and an ROC-AUC of 0.982. Median inference latency was 184 milliseconds, and the false-alarm rate was 2.4%. The recovery module correctly classified 98.6% of 500 simulated

actions into Now, Next, and Later. These results show that the prototype provides a scalable, economically viable solution to enhance grid resilience in developing power systems with limited resources and infrastructure constraints.

A cloud-based CNN-LSTM grid-collapse prediction and disaster-recovery management system can provide a unified environment for early warning, incident coordination, recoverable digital services, and organisational learning in the Nigerian power sector. However, it remains a decision-support system and not an autonomous grid-control mechanism.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors unequivocally declare no conflicts of interest.

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