DEVELOPMENT OF A DLNN MODEL FOR TRANSIENT STABILITY ASSESSMENT OF NIGERIA 28 BUS SYSTEMS

Abstract

This article proposed using a deep learning neural network (DLNN) approach to forecast transient stability. Transient Stability Assessments (TSA) have long been acknowledged as being crucial for maintaining the reliable and protect operations of power systems. The complexity of power system dynamic features has increased because to the introduction of new components like power electronics, electric vehicles, and renewable energy sources, raising severe concerns among TSA. The development of renewable energy sources is currently having an impact on the reliability and security of the electrical network. Wide area monitoring systems have been used in the electrical system, producing large amounts of data that have ushered in new approaches to resolving these problems. Transient stability issues are attracting the attention of a wide range of stakeholders due to the potential for catastrophic outages. The goal of this project is to use data collection and DLNN to look for TSA problems in the electrical system. Data from the National Control Center (NCC) Oshogbo was used to mimic the Nigerian 28 Bus system in the DIgSILENT environment. In a Python context, a feature selection pipeline is built using the Relief-F feature selection method. To forecast transient stability on Python, the chosen feature will be fed into a particular form of DLNN. The DLNN reduces the time complexity of TSA, increasing accuracy. The accuracy value produced for the Nigeria 28 bus system is 90.16 percent once the system converges after 31 epochs. The IEEE 9 bus test system is used to validate the DLNN approach, which is used

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to evaluate transient stability. The outcome of this work is compared with similar work in the conclusion in terms of some evaluation performance.

Keywords: Transient stability assessment, Deep Learning Neural Network, Long-short Term Memory, Transient stability, Power system stability, Artificial Intelligence, Neural Network, Relief F, Recurrent Neural Network.

I. INTRODUCTION

Power system stability refers to a power system's capacity to return to an equilibrium state and perform as intended in the wake of a disturbance. Rotor angle instability caused by synchronism loss has long been linked to the instability issue [4]. Transient stability is the capacity of a power system to retain synchronism in the face of significant distractions [12]. It is crucial in this case that TSA is efficient and precise. Thanks to the quick development of artificial intelligence techniques, data-driven TSA procedures have gained a lot of attention in recent years, and numerous research findings have been made public. So that relevant academia can have a better awareness of the research state, key technologies, and current difficulties in the field [7], a thorough evaluation of the available data-driven TSA approaches is required. The three types of TSA methods offered are time domain or traditional simulation method, direct method, and data-driven artificial intelligence approach. A group of highly nonlinear Differential and Algebraic Equations (DAE) characterize the behavior of synchronous generators in relation to their associated control systems, loads, renewable energy output, flexible AC transmission devices (FACTs), and the transmission network. The DAE model must be numerically solved for each condition using time domain simulations since it cannot be linearized around an operating point when a power system encounters large changes. Transient instability, which primarily causes power outages and also reduces a power system's overall performance [15]. A type of TSA known as time domain simulations is expensive and computationally difficult, especially for large power systems with an almost unlimited number of operating points and contingencies [13], [14]. The prediction model is trained using a Deep Learning technique (LSTM) and a data set for a variety of operating circumstances in order to accomplish these goals. The TSA's time complexity is decreased by the LSTM, thus enhancing prediction accuracy. The proposed model's enhanced performance is demonstrated using the Nigeria 28 Bus System, and its support by the IEEE 9 Bus System is provided.

II. TRANSIENT POWER SYSTEM STABILITY

In this study, a deep learning neural network methodology is used to build a prediction model for the transient stability of Nigeria's 28 bus system. The mathematical process for transient stability is described in this section.

1. **Transient Stability TS:** Rotor angle stability is the capacity of a synchronous machine in a power system to retain synchronism following an interruption. Power system outages may not always have the same effects on generation, so certain generators may suffer additional load as a result of adaptive operation and may slow down, while the remaining generators may accelerate up to maintain grid frequency [6–9]. The tilt of the rotor with reference to the stator changes as the generator's speed rises. The rotor continuously alternates between accelerating and decelerating in order to maintain balance between the mechanical input torque and the electrical output torque [10], [11]. By engaging in this activity, the generator's ability to produce power is reduced, and the generator, prime mover, and transformers are all damaged. As a result, the synchronous machine needs to be safeguarded [2]. The dynamic reaction of a power system to disturbances is controlled by a collection of DAE, and their compact form is:

$$x = h\,(x, y) \qquad (1)$$

$$0 = g\,(x, y) \qquad (2)$$

The state as well as the algebraic variables x and y are shown. In addition, h and g stand for the respective DAE's vectors [4], [5]. To obtain time-varying trajectories, the algebraic variables y, such as bus voltages and active power injections, and the state variables x, such as rotor angles and frequencies, are solved. This is done by employing numerical methods like the trapezoidal approach to discretize the set of differential equations (1). The generated algebraic equations and the remaining algebraic equations are solved by the Newton's technique at each time step (2). To evaluate transient stability, the dynamic trajectories over the simulation time window are monitored. This method provides an accurate assessment of temporary for a specific situation [16].

2. **Long Short Term Memory Network in TSA:** Recalling information from the past in time series requires LSTM because, LSTMs are capable of remembering previous inputs, they are useful for time-series prediction and are used to follow data across time. LSTMs, which have a chain-like structure and four interacting layers, interact in various ways. In addition to time series predictions, LSTMs are commonly used in speech recognition, music production, and pharmaceutical research [17]. LSTM is used to address the long-term dependency problem's problems. LSTM networks are a subset of RNNs. At each stage, the LSTM's has the choice to read, write, or reset the transaction [3]. Equation 3 displays the LSTM's mathematical formulas;

$$\begin{aligned}
i_t &= \sigma\,(W_{ih}h_{t-1} + W_{ix}X_t + b_i),\\
\hat{c}_t &= \tanh(W_{\hat{c}h}\,h_{t-1} + W_{cx}X_t + b_c),\\
c_t &= c_{t-1} + i_t\,.\hat{c}_t,\\
O_t &= \sigma\,(W_{oh}h_{t-1} + W_{ox}X_t + b_o),\\
h_t &= O_t\,.\tanh(c_t),
\end{aligned} \qquad (3)$$

The operator stands for the pointwise multiplication of two vectors where ct represents the state of the LSTM cell and Wi, Wc, and Wo represent the weights. The input gate chooses what new data can be entered while updating the cell state, and the output gate chooses what data can be output based on the cell state [1], [3]. Based on the connections, the LSTM cell indicated in equation 4 can be mathematically described as follows.

$$\begin{aligned}
f_t &= \sigma\left(W_{fh}h_{t-1} + W_{fx}X_t + b_f\right), \\
i_t &= \sigma\left(W_{ih}h_{t-1} + W_{ix}X_t + b_i\right), \\
\hat{c}_t &= \tanh(W_{ch}h_{t-1} + W_{ix}X_t + b_{\hat{c}}), \\
c_t &= f_t \cdot c_{t-1} + i_t \cdot \hat{c}_t, \\
o_t &= \sigma\left(W_{oh}h_{t-1} + W_{ox}X_t + b_o\right), \\
h_t &= o_t \cdot \tanh(c_t).
\end{aligned} \tag{4}$$

The forget gate determines what notifications from the cell state will be deleted. This information is stored when the forget gate, f_t, has a value of 1, and it is completely discarded when it has a value of 0. The LSTM's structure is depicted in Figure 1.

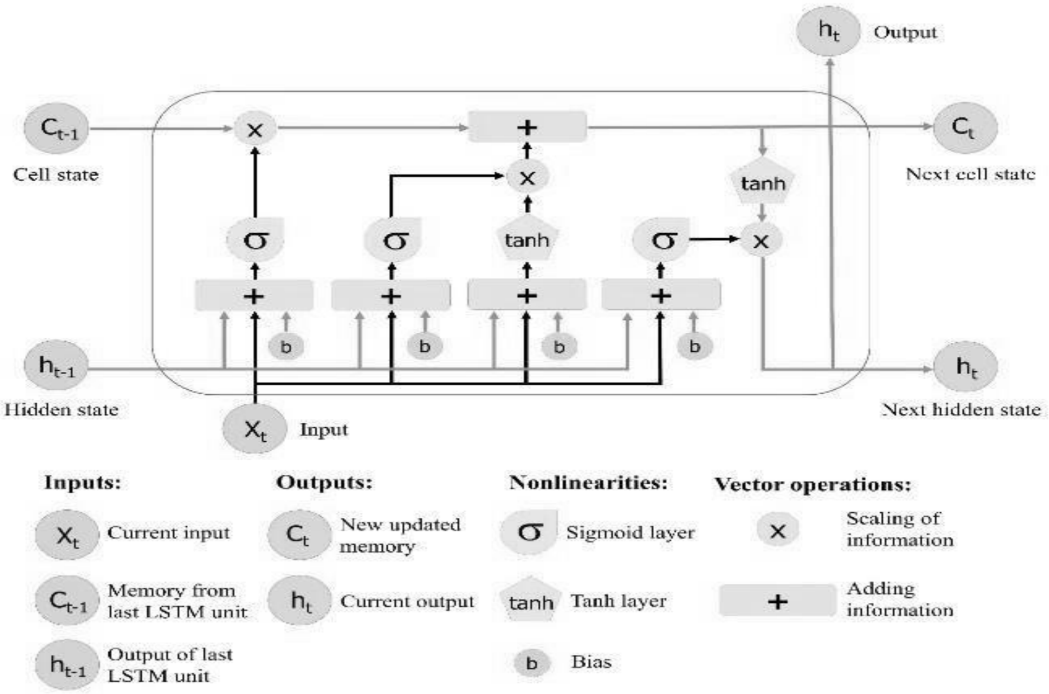

Figure 1: LSTM Network Diagram [17]

3. **Network Structure of the Model**: This study constructs a six-layer network model for a Deep learning NN for TSA, which is described below.

- Data collection: The National Control Center (NCC), Oshogbo, is where appropriate data for modeling the 28-bus Nigeria network are acquired.
- Using DIgSLIENT, the Nigeria 28 bus system was network modeled. iii. Collection of data for DLNN: The Relief-F technique is applied to remove irrelevant data from redundant ones.

- DLNN (LSTM): To perform the necessary Transient stability evaluation, a DLNN based on LSTM is modelled based on the data that is currently available, trained, tested, and validated.
- Performance evaluation: The Specificity, Accuracy, and Precision measures are then used to evaluate the performance of the LSTM model.
- Evaluate outcomes in the context of related research.
- The suggested model for evaluating transient stability is depicted in Figure 2. The TSA model has four inputs: voltage, rotor angle, reactive power, and active power.

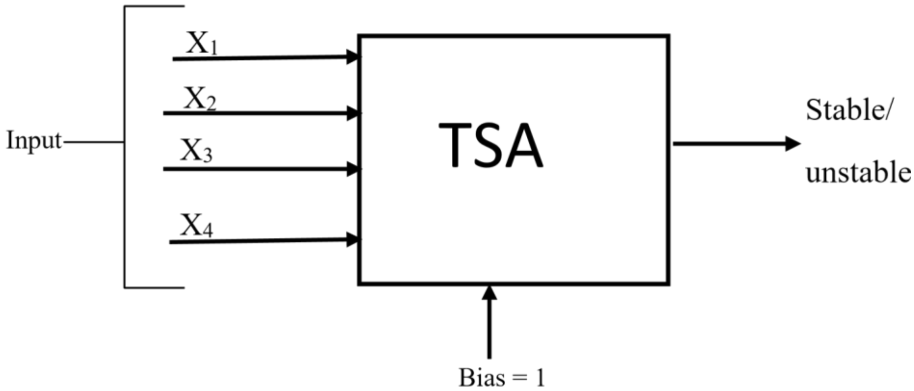

Figure 2: Schematic design model of TSA

III. RESULT AND DISCUSSION

The test is run using the LSTM and Relief-f algorithm. Python/DIgSLIENT is utilized in this study to carry out the study. The Nigerian 28-bus power system for TSA is depicted in Figure 3 below in DIgSILENT model form. For TS, information was acquired via DIgSILENT under various scenarios.

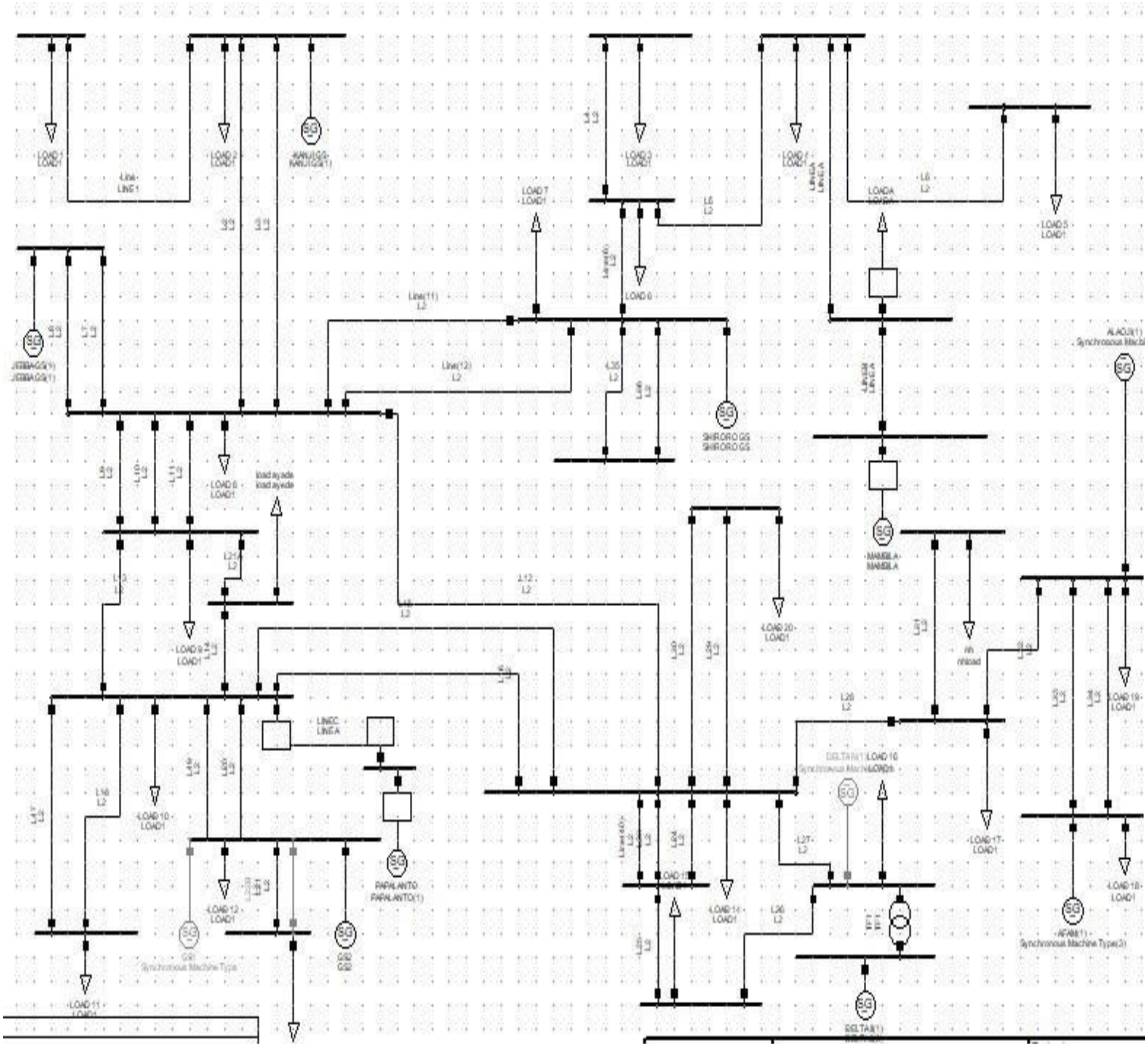

Figure 3: Modelling of Nigerian 28-Bus System

The user interface in this study allows users to import datasets, choose pertinent information from the enormous amount of data, and preprocess and choose pertinent subsets of the data using the Relief-F feature selection method. Table 1 displays loaded data for the 28 bus system in Nigeria.

Table 1: Loaded Data Nigerian 28-Bus System

V(p.u)	P(KW)	Q (KVAr)	(Ɵ)	TSA Targ
0.388583	-271.618	0.454232	-63.3957	0
0.469965	563.2468	-306.641	97.48929	0
0.255932	-209.335	151.7141	-102.012	0
0.533196	409.5992	-385.232	58.1159	0
0.147646	19.65125	190.0627	-142.138	0
0.540542	127.6128	-338.973	17.22918	0
0.220532	318.4933	72.08323	176.2186	0
0.484492	-151.327	-180.955	-25.1795	0
0.370508	535.4349	-148.529	133.0507	0
0.366197	-274.478	26.74668	-69.1091	0
0.489727	539.7334	-341.938	88.36538	0
0.209501	-156.153	174.4907	-114.545	0
0.543035	309.6819	-389.185	42.17829	0
0.154649	150.4527	153.4337	-161.475	0
0.514599	-27.5849	-260.075	-5.50633	0
0.310105	458.6298	-49.8561	150.0938	0
0.403731	-252.811	-30.6135	-54.6958	0
0.465345	553.8266	-304.05	100.1514	0
0.233219	-197.255	154.0606	-105.39	0
0.54455	350.7548	-412.666	48.70475	0
0.261644	-207.228	163.5346	-100.006	1
0.533944	476.4872	-393.262	69.36015	1
0.18805	-114.21	196.6741	-121.668	1
0.558244	357.5287	-423.106	46.91436	1
0.143834	28.34095	192.7953	-144.893	1
0.557052	193.1078	-381.217	22.91489	1

In this study, the preprocessed, Relief-f with DLNN-analyzed loaded data contains 81,802 instances classified as stable or unstable. Relief-F is used to preprocess the loaded data, and the Python LSTM is then given the specified feature. The DLNN is made up of input layers, hidden layers, and LSTM-based output layers. The model confusion matrix utilized to determine the evaluation performance of the developed model, including accuracy, sensitivity, and precision using the LSTM, is shown in Figure 5. After 31 epochs, the system converges, and the model accuracy for TSA hits 90.16 percent. Table 2 displays the model evaluation performance of the method.

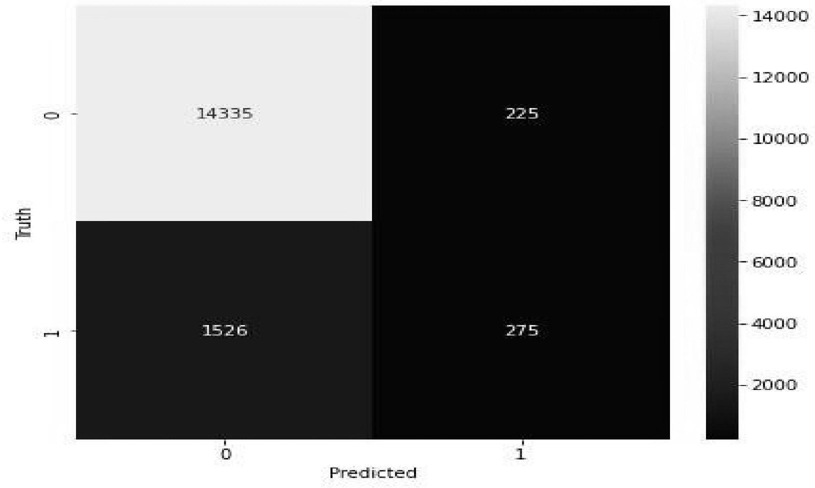

Figure 5: Confusion Matrix for the TSA Developed Model. TP=14335; TN=275; FP=225; FN=1526

Table 2: Evaluation Performance for TSA

Measure	Evaluation (%)	Derivations
Sensitivity	90.38	TRP=TP/(TP+FN)
Precision	98.45	PPV=TP/(TP+FP)
Accuracy	90.16	AC=(TP+TN)/(P+N)

The Target value of TSA acquired on DIgSILENT is displayed in Table 3 and is subsequently placed into a Long Short Term Memory (LSTM). To obtain a projected value for TSA, the LSTM is trained. Whether TSA is stable or unstable can be determined by the projected value that was attained. When the rotor angle is between 0 and 120 degrees, as predicted, the system is stable; however, when the rotor angle exceeds 120 degrees, the system is unstable.

Table 3: Target and Predicted values for TSA

S/N	Target for TSA	Predicted value\n",
"16345	0	0.0\n",
"16346	0	0.0\n",
"16351	0	0.0\n",
"16352	0	0.0\n",
"16353	0	0.0\n",
"16354	0	0.0\n",
"16355	0	0.0\n",
"16356	0	0.0\n",
"16357	0	0.0\n",
"16358	1	0.0\n",
"16359	0	1.0\n",

.

IV. RESULTS COMPARED ON IEEE 9-BUS TEST SYSTEM

The modeling of the IEEE 9 bus system in the DIgSILENT power factory is shown in this section, as indicated in Figure 5, and it is used to verify the accuracy of the TSA evaluation results. According to where the load and generator were located, the bus bars were either modelled as PV or PQ when it came to the transmission lines. The loads were PQ data-based lumped loads. The generators were accurately modeled using the appropriate data and synchronous generator characteristics. For these systems, time-domain simulations are performed using DIgSILENT. The input consists of the angle of the generator's rotor, the voltage's magnitude, as well as the amount of active and reactive power at each bus. Additionally, 10 seconds of these simulations are run with a 0.3 second temporal offset.

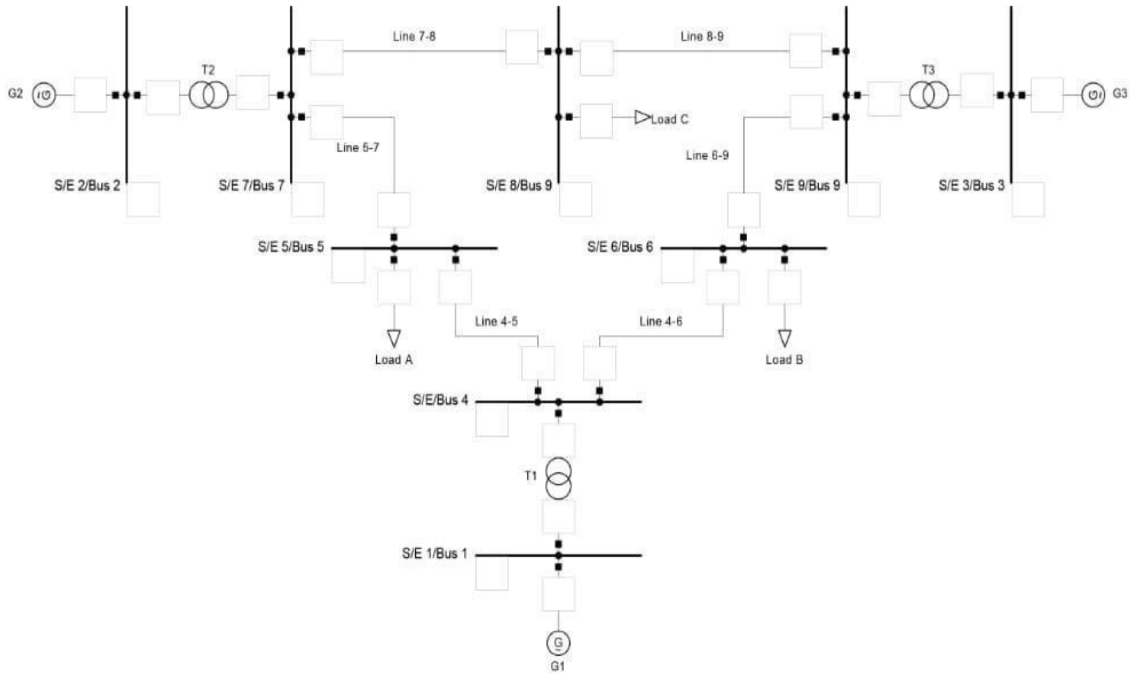

Figure 5: Modelling of IEEE 9 Bus System in DIgSILENT

The loaded data for the IEEE 9 bus system, which was created and used for training and testing, is shown in Table 4 and consists of 62,500 target values. This is because large amounts of data are required to train neural networks. The IEEE 9-Bus system recovered 18,750 testing samples and 43,750 training samples with the right goal values.

Table 4: Loaded data for IEEE 9 bus system

V(p.u)	P(KW)	Q (KVAr)	(Ɵ)	TSA Target
0.17958	-123.513	171.9536	-121.034	0
0.541271	191.1149	-377.243	26.03689	0
0.21862	312.9513	61.45572	172.7484	0
0.437684	-202.49	-101.296	-40.9198	0
0.441616	528.1544	-257.218	105.0707	0
0.210953	-162.216	160.9706	-109.329	0
0.542129	238.5471	-392.568	35.91947	0
0.194307	277.8757	75.5049	-179.199	0
0.459572	-195.994	-154.359	-34.6968	0
0.428978	542.6657	-250.911	109.4685	0
0.228289	-186.864	148.0511	-106.753	0
0.534469	254.3771	-375.392	36.6825	0
0.198982	272.5964	83.33363	179.7563	0
0.441242	-197.513	-114.59	-37.5489	0
0.445292	530.6067	-272.797	104.8101	0
0.194562	-150.778	160.4638	-113.223	0
0.542532	191.7196	-392.29	28.39765	0
0.227462	338.5404	33.06602	169.661	1
0.418274	-235.976	-78.9364	-49.4565	1
0.468614	509.4048	-308.579	91.10054	1

Figure 6 displays the TSA model confusion matrix that was utilized to compute the evaluation performance of the developed model, such as accuracy, sensitivity, and precision, using the DLNN technique. TP=2300, TN=5900, FP=4000, and FN=370 are the outcomes of the confusion matrix TSA created model. After 82 epochs, the system converges, and for TSA, the model accuracy is 65%.

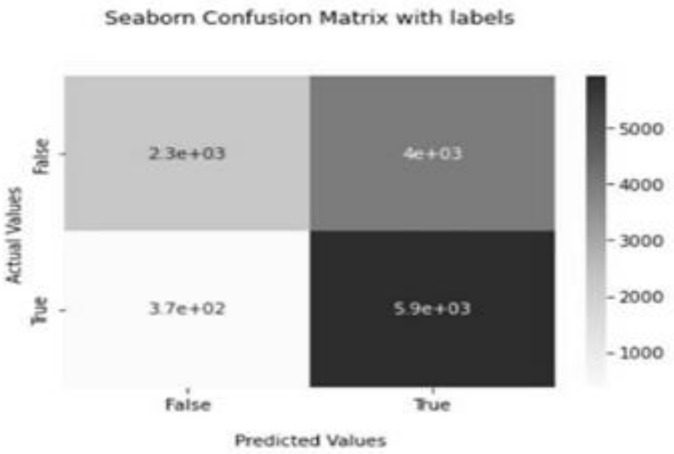

Figure 6: Confusion matrix for the TSA IEEE 9 bus system

Measure	Evaluation (%)	Derivations
Sensitivity	94	TPR=TP/(TP+FN)
Precious	86	PPV=TP/(TP+FP)
Accuracy	65	ACC=(TP+TN)/(P+N)

The results were compared with other works on TSA using various machine learning techniques. Table 6 compares the effectiveness of several techniques for predicting TSA. Accuracy, sensitivity, and precision are the main comparison criteria. The TSA's accuracy, sensitivity, and precision in the created LSTM for the 28 bus system in Nigeria have excellent evaluation performance. The low accuracy in TSA is due to the input data acquired, which included so many floats. Meanwhile, utilizing the IEEE 9 bus system, the evaluation performance for accuracy was 65%. In this scenario, random hyperparameter adjustment can be used to increase TSA accuracy, but a longer training period is necessary.

Table 6: Comparison of the performance with TSA methods

Related works on TSA	Method	Accuracy (%)	Sensitivity (%)	Precision (%)
Nigeria 28 Bus System (proposed work)	LSTM	90.16	90.8	98.45
IEEE 9 Bus System (proposed work)	LSTM	65	94	86
IEEE 39 Bus System [1].	LSTM	99.73	99.72	99.73
New England 68 Bus System [14].	SVM	97.31	_	_

V. CONCLUSION

It is now simpler to convert the current power systems into a new generation of power systems with a high penetration of renewable energy and power electronics thanks to the integration of power electronics technology and renewable energy sources. Because of this change, assessing the transient stability of power networks is rather difficult. Data driven TSA methods establish a relationship between system operational parameters and stability status before determining stability results without requiring a power system's physical model or parameter information, in contrast to conventional time domain simulation and energy function methods. The dependable and secure operation of electricity networks depends on an understanding of transient stability. For the purpose of assessing transient stability, feature-based deep learning algorithms (LSTM) are provided in this study. The study's findings will be beneficial to academics interested in the subject by providing them with a better understanding of the state of research in the fields of power system transient stability evaluation.

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