Hybrid Attack Optimization Supported Enhanced Deep Learning to Facilitate Power System Event Detection using PMU Data

Saba Kausar M. Shaikh, *Student Member, IEEE*, and Manjunath Kallamadi, *Member, IEEE*

***Abstract*—Accurate event detection is crucial for initiating control and protection measures in power systems to ensure enhanced and reliable operation. Phasor Measurement Units (PMU's) play a vital role in various functional aspects of power systems, including state estimation and intelligent protection algorithms. However, the authenticity of real-time data from PMU's must be verified before feeding it into applicable real-time algorithms to prevent undesirable or erroneous operations. This paper aims to present an efficient pre-processing methodology for identifying unwanted, incorrect, missing, or noisy PMU data to facilitate robust event detection algorithms. The proposed methodology leverages real-time data-driven deep learning techniques for authenticating incoming data. Given the high sampling rate of PMU's, the presence of extraneous data can lead to false event detection, necessitating reliable data pre-processing. Challenges identified in existing literature, such as the limitations of Steady State (SS)-Local Outlier Factor (LOF) in event detection and classification, issues with detecting line tripping and inter-area oscillations, computational and bandwidth requirements for micro-PMU installations, and false alarms resulting from inaccuracies in frequency ramp rate determination, are addressed. To overcome these challenges, this research proposes a deep learning approach that utilizes modified Deep Convolutional Neural Network (DCNN) and Long Short-Term Memory (LSTM) classifiers to classify and extract features from PMU data, enabling highly efficient detection of disturbances using real-time data. Additionally, a Hybrid Attack Optimization (HAO) technique is employed to enhance convergence rates, accuracy, and efficiency. Performance evaluation of the proposed procedure is conducted by calculating and assessing the data using metrics such as accuracy, precision, recall, System Average Interruption Duration Index (SAIDI), and System Average Interruption Frequency Index (SAIFI).**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9199

***Index Terms*—Deep Convolution Neural Network (DCNN), event detection, Hybrid Attack Optimization (HAO), Long Short-Term Memory (LSTM), Phasor Measurement Unit (PMU).**

I. Introduction

A. Background

The associate editor coordinating the review of this manuscript and approving it for publication was Gladston Moreira (*Corresponding author: Saba Kausar M Shaikh*).

Saba Kausar M. Shaikh is with the Institute of Infrastructure, Technology, Research and Management - Ahmedabad and the Institute of Information Technology - Pune, India (e-mail: saba.shaikh@aissmsioit.org).

Manjunath K. is with the Institute of Infrastructure, Technology, Research and Management - Ahmedabad, Gujarat, India (e-mail: manjunathk@iitram.ac.in).

PHASOR Measurement Units (PMU's) play an important role in power systems, offering capabilities for monitoring, detecting, and analyzing the dynamics of power system. Accurate identification of power system events, is paramount, which in turn, is possible using real-time PMU data, particularly in heavy power generating stations, where they assist in managing critical conditions such as generator trips, load disconnection failures, and line trips. Effective event detection not only enhances system visualization but also plays a pivotal role in ensuring optimal system performance through relay operations and control. However, the high sampling rate of PMU's often results in a significant amount of unbalanced data, leading to voltage, frequency, and power instability, as well as increased power distortion. Moreover, with the integration of distributed energy resources (DERs) into power systems, there is a growing need for flexible and efficient voltage and current management.

B. Brief Insights into the Literature

Numerous studies have explored event detection methodologies in PS using diverse approaches, as evidenced by an extensive literature review conducted by the authors [1]. Challenges identified in existing literature, including the limitations of conventional methods such as SS-LOF in event detection and classification, issues with detecting specific disturbances like line tripping and inter-area oscillations, and the computational and bandwidth requirements associated with micro-PMU installations, underscore the demand for advanced solutions [2], [3], [1], [4], [5].

Ameen Abdel Hai et al. [2] developed a transfer learning approach for event detection to reduce equipment costs. Here, event detection approach is based on a small amount of transferred relevant labeled data from another power system. However, achieving accurate event detection with field-recorded PMU data remains challenging. Liu Shengyan et al. [6] introduced a data-driven algorithm using the local outlier factor (LOF) to detect unstable events in the PS. The SS-LOF algorithm can be carried out to perform online monitoring in practical application. This method faces challenges when dealing with multivariable time series data from PMUs, such as voltage, frequency, and power. Jie Shi et al [7] explored the use of graph signal processing to capture spatiotemporal correlations in synchrophasor data from PMUs. The developed algorithm demonstrates excellent scalability. The event timestamps are only available at a minute-level resolution, limiting the precision of the dataset. Samira Pouyanfar et al. [8] developed an ensemble deep learning method called Automatic Video Event Detection for Imbalance data, which addresses overfitting and information loss in single models. This approach mitigates unbalanced data problems in the multimedia domain, but it involves locally connecting convolutional neural networks (CNNs). The developed framework outperforms both groups of algorithms in two datasets with different concepts, which demonstrates it's advantage effectiveness for video event detection. This increases the training speed with the elimination of more parameters in the network. Wang Weikang et al. [4] introduced deep learning methods that utilize variable frequency and relative angle values to predict images as input. The model achieves fast decision making. Although the model achieves fast decision making, the presence of complex spatiotemporal characteristics poses challenges in detecting frequencies accurately. Cui Mingjian et al. [9] presented a PMU-supported event detection method called Dynamic Programming-Swinging Door Trending (DPSDT), which compresses real time PMU data using a tunable door width. The developed method is capable of identifying the significant changes in both the decomposition coefficients and the normalized wavelet energy (NEW) metric. However, the performance of the PMU event reorganization fails to provide the startup time of PMU events, leading to a loss of information. PawelDawdowski et al. [10] developed an event detection method using auto encoders and the Fourier Transform series. The major difference is that the linear auto-encoder is able to learn it's filter weights by providing the signal. They generated three signal datasets, but the major faults in the Phasor calculation caused the loss of local event information during detection. Ravi Yadav et al. [11] developed an event detection method using the Teager-Kaiser energy operator (TKEO). The method results accurate event detection and its classification for multiple events in the presence of intermittent sources in a system. This method exhibits better performance with single units compared to multiple units, but the complexity of various classes in terms of power line locations or magnitudes poses challenges. Dazhong Ma et al. [12] introduced a multidimensional matrix-based method using spectral theory and a portioning algorithm for PS event detection. This method is applicable for both distribution and transmission systems. However, the inherent nonlinearity, complexity and uncertainty of the PS event result in poor performance. ShraddhaJadhav et al. [13] developed a trend filter technique for achieving accurate detection in real-time along with event classification using synchrophasor data. The most important attribute of frequency signals is; it is stationary under normal operating conditions. However, classifying events with multiple frequency modes remains challenging. Armin Aligholian et al. [14] presented a Generative Adversarial Network Scoring Method for event detection in Micro-PMU data. However, the statistical method only captures the step change. Yuxuan Yuan et al. [15] presented a two-stage learning-based network for real-time event identifications and CNNs with assistance from spatial pyramid pooling (SPP) are developed to reliably and efficiently identify operation events. Although the models achieve efficient results, more than 10% of data suffers from quality issues. Mohammad Reza Shadi et al. [16] developed an LSTM model and a Recurrent Neural Network (RNN) model to find and distinguish Frequency Disturbance Events (FDEs) with a high degree of accuracy. The convergence rate on the classification of FDEs and the location of Generator Trip (GT) and Load Disconnection (LD) on the validation data is higher than the training data. The suggested models were less accurate in locating FDEs. Xianjun Xia et al. [17] developed a Random Forest classification based Acoustic Event detection using Contextual information and Bottleneck features. Here, the global bottleneck features can capture the important contextual information with minimal input dimension. However, only the prior knowledge of the event and boundary information is utilized.

C. Description of Suggested Methodology

In response to the aforementioned limitations/challenges, this research endeavors to develop a deep learning model for event detection using PMU data. The objective is to pre-process unbalanced and missing PMU readings using a curve-fitting algorithm with a polynomial equation of the anomaly function, thereby enhancing the quality of PMU feature vectors. Subsequently, labels and features are extracted from statistical features, and classification is performed using a Hybrid Attack Optimization (HAO) algorithm integrated with a deep CNN-LSTM classifier. The proposed methodology collects required procedural aspects for processing unbalanced PMU feature vectors, reducing noise and delay time, and enhancing overall efficiency. The HAO algorithm, a novel advancement combining Falcons and Echo Bat optimization, demonstrates high convergence rates, fewer parameters, and improved tuning of optimal solutions, thereby paving way for enhancing the robustness and effectiveness in identifying the unwanted events.

D. Paper Organization

The paper is organized as follows: Section 1 provides an overview of the research objectives and context. Section 2 elaborates on the proposed methodology of DCNN-LSTM-based Hybrid Attack Optimization. Section 3 discusses the implementation of the proposed methodology with result analysis, and Section 4 concludes the paper.

II. Methodology of DCNN-LSTM-Based Hybrid Attack Optimization

This research focuses on developing an initial stage of event detection model using deep learning techniques with PMU (Phasor Measurement Unit) data. The PMU dataset initially suffers from data imbalance and missing values, which can hinder event detection. To address these challenges, a comprehensive data pre-processing methodology is suggested before applying intelligent control algorithms. Fig. 1 provides an overview of proposed methodology, including data pre-processing, the modified DCNN-LSTM classifier, and the HAO optimization technique for event detection [18]. The overview of the proposed methodology is presented below.

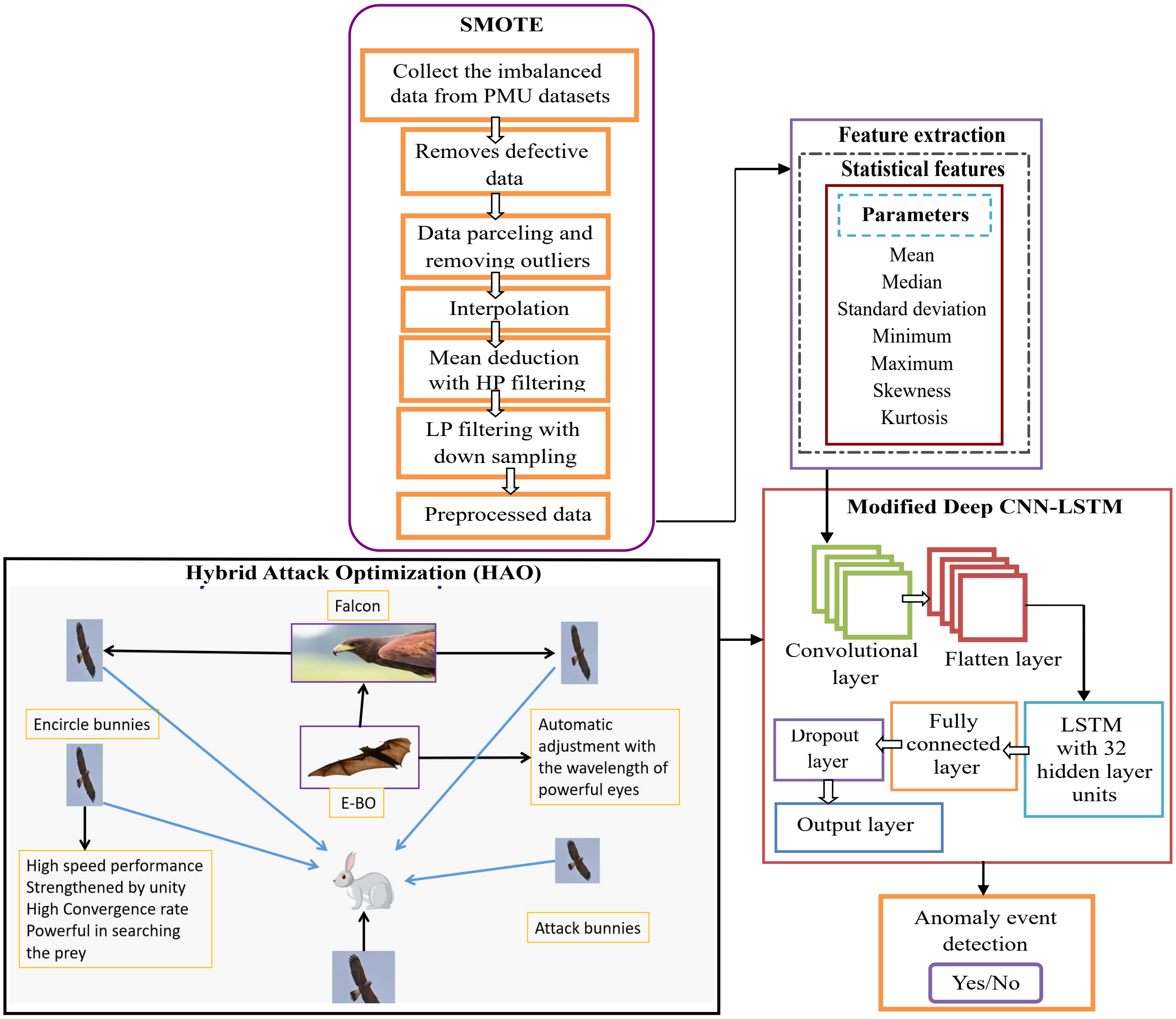

Fig. 1. Overview of the proposed methodology employing HAO supported DCNN-LSTM approach for data filtering.

1) Data Balancing with Curve-Fitting Algorithm: In this, data imbalance is tackled by using a curve-fitting algorithm that employs polynomial equations to balance the dataset.

2) Label and Feature Extraction: Labels and features are extracted from statistical features computed from PMU data, enhancing the model's ability to detect events.

3) Transformation to Tensor Data: A large number of data points are transformed into tensor data, which is combined with the statistical features extracted from the PMU data.

4) P-Center Formulation and Normalization: Data undergoes P-center formulation and normalization to simplify representation while preserving essential information.

Subsequently, the resultant data is fed into the modified DCNN-LSTM classifier. It then optimizes the classifier's hyper parameters using the proposed hybrid attack optimization technique, combining Falcons' optimization with bat echolocation for event detection. This methodology is then implemented in MATLAB and its performance is compare with existing techniques. The suggested methodology is then assessed using accuracy, precision and recall metrics, quantifying its effectiveness in data filtering.

A. PMU Data Pre-processing and Data Balancing

In this deep learning-based data filtering supported event detection model, the authors addressed imbalance and numerical feature vectors in PMU data. This research aims to identify disturbances in the PMU data under unexpected real power events. Pre-processing techniques are applied to the PMU data to handle imbalanced features. The pre-processing step and its contributions to the proposed research are explained below.

1) Significant Contributions: The PMU data contains imbalanced features, including voltage and current values, as well as discrete data from relay logs, forming structured heterogeneous data.

- Fig. 1 illustrates the PMU datasets, which consists of raw data in the form of imbalanced sets
- The authors pre-process Synchro Phasor data by removing defective data, bundling datasets, eliminating outliers, interpolating missing samples, and applying trend functions
- During missing data periods, filters capture highly sensitive data ranges
- Outliers are removed, and missing samples are interpo-

lated.
- Data is classified into parcels, and processed individually to remove outliers and maintain temporal and geographic correlations
- The Synthetic Minority Over-Sampling Technique (SMOTE) is employed to balance unbalanced datasets.
- SMOTE transforms the training dataset, reducing noise samples [19]. The dataset used in this research contains minimum number of unbalanced data hence to balance this unbalance data the SMOTE function is chosen.

B. Modified Deep CNN-LSTM Classifier with Hybrid HAO

In this research, the Modified Deep CNN-LSTM classifier is employed to overcome limitations found in previous studies. This classifier combines Deep Convolutional Neural Networks (DCNN) and Long Short-Term Memory (LSTM) networks for handling long-term dependencies in sequential data. Also to address issues with unbalanced hyperparameters in the DCNN-LSTM classifier and enhance event detection accuracy, Hybrid Attack Optimization (HAO) method is incorporated. HAO combines the optimization techniques of Falcons and Echo Bat Optimization (E-BO). Its advantages include faster computation, cost-effectiveness, and quicker response with fewer parameters.

1) The CNN Component:
- Extracts spatial patterns or features relevant to classification from input data.
- Enhances spatial structure extraction.

2) The LSTM Component:
- Addresses gradient disappearance in deep networks during training.
- Captures and retains long-term dependencies in sequential data.
- Improves overall performance.

3) The HAO Component:
- The Falcon algorithm is known for its simplicity, fast convergence, strong local search capabilities, and a smaller number of parameters.
- On the other hand, the E-BO algorithm is characterized by its flexibility and its ability to solve mathematical and data mining problems.
- By incorporating the HAO algorithm, the DCNN-LSTM classifier can effectively capture and attack prey within a short duration of time, improving the accuracy of event detection.

4) Applicability: Proven effectiveness in various domains like natural language processing, machine translation, and emotional analysis where sequential data is crucial

The DCNN-LSTM, consists of four main layers: input layer, convolutional layer, pooling layer, and output layer. Each layer performs a specific function to extract features and generate predictions.

The functional aspects of various layers in the algorithm are outlined as follows.

It creates a dimensional representation of the input data (symbolized as i_t) and outputs data (symbolized as g_{t-1} over time $(t-1)$), capturing temporal dependencies.

TABLE I
FUNCTIONS OF VARIOUS LAYERS

Layer	Function
Input Layer	Receives input data
Convolutional Layer	Extracts features
Pooling Layer	Reduces dimensionality and retains essential features
Fully Connected Layer	The softmax function is used to connect CNN and LSTM layers
Output Layer	Generates the final output based on high-order features
LSTM Layer	Manages memory units and gates for information flow control

5) LSTM Gates:
- Forgetting Gate (0 or 1): Retains or forgets information from the previous cell state.
$$f_t = (W_f[h_{t-1}, x_t] + b_f) \tag{1}$$
Where $f_t\epsilon$ [0.1] is the output of the forgetting gate, 0 positions indicate information task is completed 1 means that the process of the execution returned, $w_f$and b_f, mean bias and weight matrix. The input gate symbolizes the updating degree of current information in a cell, the sigmoid function is updated by the value of the tan h function is used to generate the state variable C_t and i_t, σ means sigmoid function [11].
- Input Gate: Controls new information flow into the cell.
$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{2}$$
- Output Gate: Determines output based on current cell state.
$$o_t = \sigma(W_0.\lfloor h_{t-1}, x_t \rfloor + b_0) \tag{3}$$
$$h_t = o_t.tanh(C_t) \tag{4}$$
Where o_t means input gate output and h_t is the output value for the output layer. These equations control the flow of information and update cell states. However, some hyper parameters fail to detect events in imbalanced data properly. These hyper parameter values are input into the Hybrid Attack Optimization (HAO) for further refinement. Figure 1 illustrates the process of falcons attacking and encircling bunnies from both the sky and the ground. Algorithm 1 describes the HAO process.

III. CASE STUDY

The successful implementation of advanced algorithms for power system analysis relies heavily on the availability of reliable data sources, particularly from PMU's. In the context of Maharashtra's 400kV grid, equipped with 21 PMU's distributed across various substations, accessing pertinent data is crucial for accurate analysis and decision-making.

A. Identification of Crucial Data

Among the several State Load Dispatch Centres (SLDCs) in Maharashtra, Lonikand SLDC emerges as a strategic choice for this research endeavor. Its location within the grid ensures comprehensive coverage and accessibility to critical data points necessary for algorithm development and validation.

S. No	HAO Algorithm
1.	Start
2.	Initialize the parameters
3.	Evaluate the Fitness Function
4.	Solution Update
5.	While do $t > t_{max}$
6.	If $r \leq 0.9$ then Exploration Phase
7.	If $n \geq 0.5$
8.	$y_j^{t+1} = y_{rd}^t(1 - g_1) + 2g_1 g_2 . y^t + g_3 . v_{rd}$
9.	else ($n < 0.5$)
10.	$y_j^{t+1} = y_q^t - y_{avg} - g_3(LBO + g_4(HBO - LBO)) + v_i^t$
11.	Else if $r > 0.9$ then Exploitation Phase
12.	If $n \geq 0.5$
13.	$y_j^{t+1} = y_q^t - \frac{\partial}{\partial t} y^t + \frac{\partial^2}{\partial t} d^t$
14.	Else $n < 0.5$
15	$Y_j^{t+1} = y_i^t(1 - \beta + \delta) - \delta y_m + y^* . \beta - y_q^t$
16.	Re-evaluate the fitness function
17.	Declare the best solution
18.	Terminate the process
19.	End While

1) PMU Distribution Overview: As seen in Fig. 2, the 400 kV grid in Maharashtra hosts a network of 21 PMUs strategically deployed across different substations. The distribution includes;

- 5 PMUs at Chandrapur SLDC
- 7 PMUs at Padghe SLDC
- 4 PMUs at Lonikand SLDC (highlighted in Fig. 2)
- 2 PMUs at Kalwa substation
- 3 PMUs at Kolhapur substation

The selection of Lonikand SLDC as the primary data source stems from its pivotal position within the grid architecture. By leveraging data from Lonikand SLDC, researchers can capture comprehensive insights into grid dynamics and performance, facilitating the robustness and efficacy of the algorithm under development.

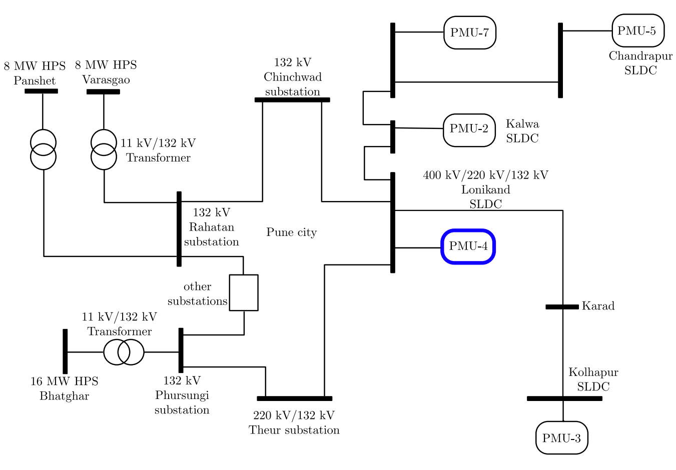

Fig. 2. Single-line diagram of real-time system from where data is collected.

A real-time three-day dataset of the considered system is chosen, which encompassed a power failure event. The threshold levels for sag and swell detection were taken to be 0.9 per unit (p.u.) and 1.1 p.u., respectively. Subsequent to the execution of the analysis using MATLAB, the data samples are plotted in Fig. 3. The analysis results reveal the presence of power quality events in the 400 kV grid, including a notable power failure event. These findings underscore the importance of continuous monitoring and analysis using PMUs to maintain grid stability and reliability.

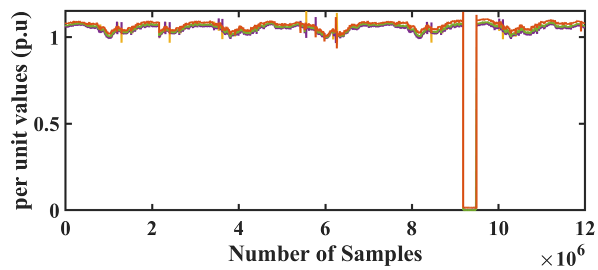

Fig. 3. Data set with a power failure event

B. Overview of Real-time Data

The dataset comprises of a collection of time series data related to different electrical grid situations including instances with no faults and occurrences of short circuits. It is fact that the robustness of any learning based approach depends on the number of trainings carried out by considering applicable and real-time data sets. The datasets associated with the major events experienced by the considered power system is very limited and hence may provide limited insights to evaluate the efficacy of the proposed methodology. However, the additional datasets will always strengthen the algorithm to avoid any mislead for data filtering supported power system event detection. Hence, additional data sets are also considered by simulating various scenarios using ePMU DSA tools pertaining to 400 kV transmission system with a resolution of 120 data samples per second. The study is performed on a digital platform using MATLAB with Windows 10 operating system having 8 GB RAM [20]. The parameters of the DCNN is Kernel size as 3, Stride size as 1, Convolution layer size 5, ReLU as activation function, ADAM as default optimizer, leraning rate as 0.01 and Batch size as 64.

C. Results and Discussion

This section provides an overview of the results obtained using the DCNN-LSTM classifier with HAO for handling unbalanced data from PMU datasets. Performance analysis was conducted based on parameters such as accuracy, precision, recall, F1-score, System Average Interruption Duration Index (SAIDI), and System Average Interruption Frequency Index (SAIFI) [21]. Standard formulae to calculate these were used. Evaluation of HAO in terms of accuracy, precision, F1-score, SAIDI, and SAIFI based on training percentage (TP). The effectiveness of the event detection method is demonstrated with PMU data references. The performance analysis at TP 40, 50, 60, 70, and 80, with epoch values of 20, 40, 60, 80, and 100.

In particular, the developed technique achieved an accuracy of 98.47% at epoch 100 and TP of 80%; this high accuracy highlights the model's ability to correctly predict events. The developed approach shows a precision of 98.29% at TP of

80% for epoch 100. This indicates the model's capability to accurately identify true positive instances among predicted positives. For epoch 100 at TP 80%, the F1-score of the suggested system is 98.65%. This strong F1-score indicates that a significant percentage of the real positive cases were captured by the model. The developed method's SAIDI at TP of 80% for epoch 100 is 2.00, suggesting a comparatively short average duration of interruptions. Furthermore, the developed method's SAIFI for epoch 100 is 1.00 at a TP of 80%, indicating a low average interruption frequency. These values highlight the efficiency of the method in handling unbalanced data with high-performance values.

D. Performance Analysis based on K-fold

Evaluation of HAO in terms of accuracy, precision, F1-score, SAIDI, and SAIFI based on K-fold with various epoch values (20, 40, 60, 80, 100) and k-fold values (5, 6, 7, 8, 9, 10).

The developed method acquired a high accuracy of 97.36% at epoch 100 and K-fold 10, demonstrating the model's capacity for accurate event prediction. With a K-fold 10 for epoch 100, the developed method demonstrates a precision of 98.69%. This shows how well the model can distinguish real positive cases from anticipated positives. The proposed system has a 97.84% F1-score for epoch 100 at K-fold 10. This excellent F1-score suggests that the model was able to account for a sizable portion of the true positive cases. The developed approach shows a relatively low average time of interruptions, with a SAIDI of 1.92 at K-fold 10 for epoch 100. Additionally, the developed method's SAIFI for epoch 100 is 1.00 at K-fold 10, suggesting a low average frequency of interruptions. These values emphasize the method's efficiency in handling unbalanced data with high performance values.

E. Comparison with Other Methods

The effectiveness of the proposed HAO-DCNN-LSTM is evaluated through a comparative analysis with conventional techniques, including K-Nearest Neighbor (KNN) [22], Support Vector Machine (SVM) [23], Random Forest (RF) [17], Artificial Neural Network (ANN) [24], DCNN-LSTM [25], Harris Hawk Optimizer based DCNN-LSTM (HHO-DCNN-LSTM) [17], and Bat Algorithm Optimizer based DCNN-LSTM (BAO-DCNN-LSTM) [13].

TABLE II
COMPARATIVE DISCUSSION BASED ON TRAINING PERCENTAGE

Methods	Metrics				
	Accuracy%	**Precision%**	**F1-score%**	**SAIDI**	**SAIFI**
KNN	90.72	91.29	91.17	1.93	0.92
SVM	91.5	91.92	91.96	1.94	0.93
RF	92.05	92.56	92.51	1.94	0.93
ANN	93.06	93.2	93.52	1.95	0.95
DCNN-LSTM	93.84	93.84	94.31	1.96	0.96
HHO-DCNN-LSTM	94.62	94.47	95.09	1.96	0.97
BAO-DCNN-LSTM	95.4	95.11	95.87	1.97	0.98
HAO-DCNN-LSTM	98.47	98.29	98.65	2	1

1) Comparative Analysis based on Trained Percentage Data: Table II highlights the superiority of the proposed HAO-DCNN-LSTM method over other methods in terms of accuracy, precision, F1-score, SAIDI, and SAIFI, with improvements ranging from 3.12% to 7.87% compared to existing methods.

When compared to previous approaches, (refer Table II) such as KNN, SVM, RF, ANN, DCNN-LSTM, and HHO-DCNN-LSTM, the proposed method shows improvement of 7.87%, 7.08%, 6.52%, 5.5%, 4.7%, 3.91%, and 3.12%, respectively by attaining an accuracy of 98.47 % at TP 80%. Similar to this, precision at TP 80 is 98.29%, and when compared to the previously mentioned existing methods, it shows an enhancement of 7.13%, 6.48%, 5.83%, 5.18%, 4.54%, 3.89%, and 3.24%, respectively. When compared to the previously described existing approaches, the F1-score at TP 80 is 98.65%, and it is improved to 7.58%, 6.78%, 6.22%, 5.19%, 4.40%, 3.61%, and 2.81%, respectively. The developed method attains SAIDI of 2.00 at TP 80% which shows an improvement of 3.61%, 3.28%, 2.95%, 2.62%, 2.295, 1.97%, and 1.64%, respectively over other compared methods. Similarly, the developed method's SAIFI is 1.00 at TP 80%, which shows a significant increase of 8.02%, 7.08%, 6.615, 5.205, 4.265, 3.32%, and 2.38% over other compared methods. According to these findings, the HAO approach continuously beats the other approaches, offering improved SAIDI, SAIFI, recall, accuracy, and precision scores for event prediction.

The analysis based on training percentage demonstrates that the HAO-DCNN-LSTM method consistently outperforms existing methods, providing higher accuracy and performance values for event detection. The generated values are presented in Table 2 below.

TABLE III
COMPARATIVE DISCUSSION BASED ON K–FOLD

Methods	Metrics				
	Accuracy%	**Precision%**	**F1-score%**	**SAIDI**	**SAIFI**
KNN	91.21	91.82	91.67	1.85	0.92
SVM	91.98	92.45	92.44	1.85	0.93
RF	92.74	93.07	93.20	1.86	0.94
ANN	93.46	93.66	93.93	1.86	0.95
DCNN-LSTM	94.27	94.32	94.74	1.87	0.96
HHO-DCNN-LSTM	95.03	94.94	95.50	1.88	0.97
BAO-DCNN-LSTM	95.79	95.57	96.27	1.88	0.98
HAO-DCNN-LSTM	97.36	98.69	97.84	1.92	1

2) Comparative Analysis based on K-fold: Comparative analysis of the developed HAO-DCNN-LSTM method against KNN, SVM, RF, ANN, DCNN-LSTM, HHO-DCNN-LSTM, and BAO-DCNN-LSTM, while varying K-fold values. Table II gives improvements in accuracy, precision, F1-score, SAIDI, and SAIFI when compared with other methods.

The suggested method achieves an accuracy of 97.36% at K-fold 10, which shows an improvement of 6.79%, 6.01%, 5.23%, 4.49%, 3.67%, 2.89%, and 2.11% when compared to earlier approaches, such as KNN, SVM, RF, ANN, DCNN-LSTM, and HHO-DCNN-LSTM. Comparing this to the previously mentioned existing methods, the precision at K-fold 10 is 98.68%, and there has been an improvement of 6.96%, 6.32%, 5.69%, 5.09%, 5.09%, 4.43%, 3.79%, and 3.16% respectively. The F1-score at K-fold 10 is 97.84%, and it is enhanced to 6.31%, 5.52%, 4.74%, 3.99%, 3.17%, 2.39%, and 1.60%, in comparison to the previously reported existing methodologies. The developed method achieves a SAIDI of 1.92 at K-fold 10, indicating improvements over other compared methods of 3.69%, 3.35%, 3.02%, 2.70%, 2.35%, 2.01%, and 1.68% respectively. Similar to the other examined methods, the developed method's SAIFI is 1.00 at K-fold 10, indicating a significant increase of 7.46%, 6.50%, 5.55%, 4.655, 3.65%, 2.70%, 1.74%. The proposed method consistently achieves higher performance values, indicating its superiority. HAO-DCNN-LSTM not only delivers high performance but also exhibits faster computation speed. Overall, the HAO-DCNN-LSTM model proves effective in achieving high-performance results and efficient computation for event detection.

The analysis is conducted by varying the K-fold iteration values, and it demonstrates that the hybrid attack optimization coupled with the deep CNN-LSTM classifier outperforms existing methods, achieving the best values. The achieved values are summarized in Table III.

TABLE IV
RUN TIME ANALYSIS OF HAO-DCNN-LSTM

Methods	Run time (s)
KNN	0.90
SVM	0.89
RF	0.70
ANN	0.70
DCNN-LSTM	0.70
HHO-DCNN-LSTM	0.70
BAO-DCNN-LSTM	0.59
HAO-DCNN-LSTM	0.54

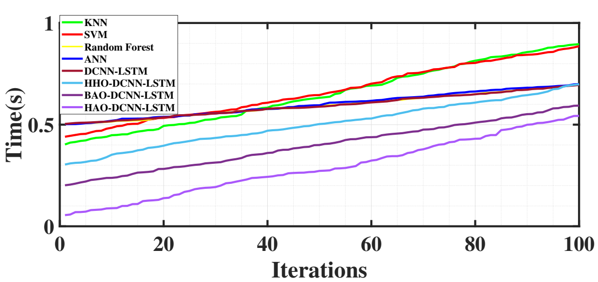

Fig. 4. Plot showing execution times of methods with iterations.

F. Run Time Analysis

The comparison of execution times among the considered methods is conducted across multiple iterations to showcase the efficacy of the developed HAO-DCNN-LSTM. The results show that the model requires much less run time than other existing approaches. At iteration 100, the suggested solution has the lowest runtime of 0.54 s when compared to other existing approaches. These results are depicted in Table IV. This short runtime is made possible by the use of HAO in DCNN-LSTM. Tuning the classifier using HAO speeds up the execution and improves its efficiency. The run time analysis of the model is depicted in Fig. 4.

G. Convergence Curve Analysis

The convergence analysis of the HAO-DCNN-LSTM framework is illustrated in Fig. 6. The convergence rate of the proposed HAO-DCNN-LSTM model is conducted across multiple epochs to showcase the loss of the HAO-DCNN-LSTM model. At 300 epochs the proposed model attains the lowest loss of 0.17.

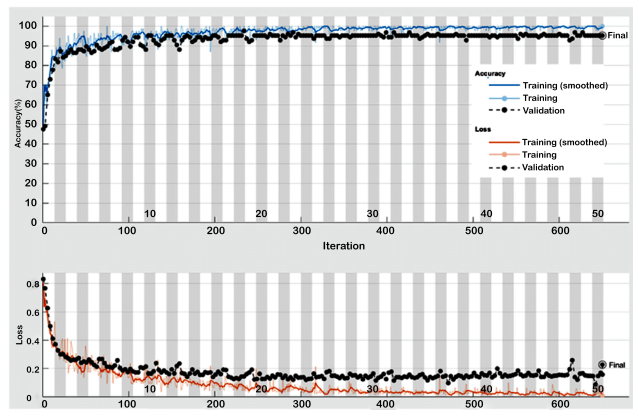

Fig. 5. Convergence Curve Analysis of HAO-DCNN-LSTM model.

H. Statistical Analysis

The statistical analysis is carried out in terms of best, mean, and variance for precision, sensitivity, and specificity. Here the results of the proposed HAO-DCNN-LSTM is compared with the existing methods KNN, SVM, RF, ANN, DCNN-LSTM, HHO-DCNN-LSTM, BAO-DCNN-LSTM. Table V includes the statistical analysis of the proposed model compared with the existing model.

IV. CONCLUSION

This paper proposed a deep learning approach to support power system event detection using real-time PMU data. In specific, a validation approach for data filtering is presented against the presence unwanted and noisy data. This, in turn, enhances reliability of real-time control algorithms in practical power system. The proposed method utilized deep convolutional neural networks (DCNN) and long short-term memory (LSTM) to effectively detect and classify events in power system.

To address the issue of unbalanced data, the SMOTE function was employed to achieve data balance by generating synthetic samples. This, in turn, improves the accuracy and precision for unbalanced datasets by separating labels and features from the dataset. Further, statistical features are extracted from the pre-processed data to reduce the dimensionality of the data and to improve the efficiency of the model.

The hybrid attack optimization (HAO) technique was incorporated to enhance the performance of the deep learning model

TABLE V
STATISTICAL ANALYSIS OF HAO-DCNN-LSTM

Methods/Metrics		**KNN**	**SVM**	**RF**	**ANN**	DCNN-**LSTM**	HHO-**DCNN-LSTM**	BAO-**DCNN-LSTM**	HAO-**DCNN-LSTM**
Best	Accuracy%	90.72	91.50	92.05	93.06	93.84	94.62	95.40	98.47
	Precision%	91.29	91.92	92.56	93.20	93.84	94.47	95.11	98.29
	F1-score%	91.17	91.96	92.51	93.52	94.31	95.09	95.87	98.65
	SAIDI	1.93	1.94	1.94	1.95	1.96	1.96	1.97	2.00
	SAIFI	0.92	0.93	0.93	0.95	0.96	0.97	0.98	1.00
Mean	Accuracy%	85.94	86.72	87.28	88.28	89.06	89.78	90.46	93.79
	Precision%	86.39	87.02	87.66	88.30	88.93	89.57	90.21	93.39
	F1-score%	86.37	87.16	87.72	88.72	89.51	90.29	91.07	94.74
	SAIDI	1.88	1.89	1.89	1.90	1.91	1.91	1.92	1.95
	SAIFI	0.86	0.87	0.88	0.89	0.90	0.91	0.92	0.96
Variance	Accuracy%	11.41	11.41	11.35	11.38	11.40	12.07	12.60	10.94
	Precision%	12.01	12.01	12.01	12.00	12.00	12.00	12.00	12.00
	F1-score%	11.52	11.52	11.47	11.50	11.52	11.52	11.52	9.57
	SAIDI	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012	0.0012
	SAIFI	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0009

by tuning the parameters of the modified DCNN-LSTM classifier. The HAO-DCNN-LSTM approach demonstrated high efficiency, accuracy, fast response. Accuracy, precision, F1-score, SAIDI, and SAIFI values of 98.47%, 98.29%, 98.65%, 1.00, and 2.00, respectively are observed.

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Mrs. Saba Kausar. M Shaikh is an Indian author born in Maharashtra. She has completed her M.Tech in Electrical Power System from College of Engineering- Pune (COEP) affiliated to the University of Pune. Currently, she is a research scholar in Institute of Infrastructure, Technology, Research and Management (IITRAM)- Ahmedabad, Gujarat. She completed her B.E in Electrical Engineering from University of Pune in the year 2002. She has also completed her Diploma in Electrical Engineering (DEE) from Cusrow Wadia Institute of Technology (CWIT)- Pune. She has been awarded a gold medal in Electrical Power subject of DEE. She has secured sixth rank in the University of Pune during her third year of under-graduation. She is working as an Assistant Professor in AISSMS Institute of Information Technology (IOIT) – Pune. She has a total experience of 16 years in teaching and 2 years in industries like Reliance Industries Ltd. She has received the Cambridge International Certificate for Teachers and Trainers. This certificate has been awarded by the University of Cambridge International Examinations for achieving the required standard (Distinction) in the following units:Developing a new teaching approach, facilitating active learning, reflecting on practice. She has a few publications in ieeexplore and a few books to her credit. Ms. S M Shaikh is a member of the Indian Society for Technical Education (ISTE)- LM 67653, Institution of Engineers (India) (IEI) Member M-157483-8, and IEEE Student Member 98790765.

Dr. Manjunath Kallamadi is currently working as an Assistant Professor in the department of Electrical and Computer Science Engineering department at Institute of Infrastructure, Technology, Research and Management (IITRAM) Ahmedabad, Gujarat. He completed his Ph.D. in Power and Energy Systems (2011-2016), from Indian Institute of Technology Hyderabad. He has done his M. E Power Systems (2009-2011), from Bengal Engineering and Science University, Shibpur. (Currently, Indian Institute of Engineering Science and Technology IIEST, Shibpur). Dr. Manjunath's research interests include energy management in an AC microgrid, reactive power compensation in Power Systems, Microgrids and Distributed Generation, Stability and Control of Power and Energy Systems.