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Diagnosis Of South-Western Nigeria Electrical Power Network Using Optimized CNN-PMA Model

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Abstract- Accurate diagnosis of electrical network is essential in system stability. However, existing models such as state of the art and artificial intelligence based require improvement due to their rate of response and accuracy of their diagnosis. Hence, this research proposed optimized convolutional neural network with pelican mayfly algorithm optimization CNN-PMA model for adequate diagnosis of electrical network in south western Nigeria (SWN). Pelican optimization was applied to mayfly in order to achieve a balance in exploration and exploitation of mayfly and was then used to select optimal hyper-parameters of CNN. CNN-PMA was designed and implemented to detect, classify and predict electrical faults in SWN using MATLAB software packages toolboxes such as deep learning and optimization and data division was achieved using random sampling cross validation technique. Confusion metrics was adopted to analyze fault detection and classification. The performance of CNN-PMA was evaluated on a standard IEEE 9-Bus system using MAPE, MSE, SNR, PSNR, RMSE. The performance of the proposed model is excellent compared to conventional CNN and other existing models.

Key words: Diagnosis, artificial intelligence, CNN-PMA, South-western Nigeria.

I. INTRODUCTION

Electrical power networks are increasing in sizes and becoming complex in all sectors such as: generation, transmission and distribution due to population increase and technological advancement. As the sizes increase, the probability that faults will occur increases. In view of this, timely diagnosis of the system is required in order to reduce effects of faults occurrences on the system. Various models had been developed to detect, classify and predict electrical faults but their performance can be improved in term of response, accuracy and efficiency. This work is aimed at using optimization of CNN method for timely diagnosis of electrical network using South-Western Nigeria (SWN) as case study. Mayfly and Pelican optimization algorithms were hybridized to have a stronger optimization technique (Pelican Mayfly Algorithm PMA) able to select optimal hyper-parameters of CNN.

Optimizer are algorithms used in machine learning to obtain the best solution among possible solutions under some constraint functions (Yang and Karamanoglu, 2016). The use of appropriate algorithm for a formulated optimization problem determines the effectiveness of the solution and the speed at which the solution is obtained (Blum and Roli, 2003). CNN is a multi-layer neural network which comprises several convolutional layers and pooling layers alternately and one or more full connection layers connected to classify the image features generated by the previous layers. CNN has advantages of processing large amount of data with less computational cost. Therefore, it is used in solving various detection, classification and prediction problems (Chen et al., 2018: Jing et al., 2017: Bracale et al., 2017).

1.1 Electrical Faults

Electrical fault is defined as abnormal condition in power system when there is a decrease in the basic insulation strength between lines conductors or line conductors and earth, or any earthed screens surrounding the conductors (Izykowski, 2011).

Causes of Faults in Electrical Network: The causes of faults can be internal or external. These comprises: Lightning, Pollution, Wildfires, Ageing, Tree contact, Animals and birds and Vandalism.

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Consequences of Electrical Faults: The short circuit fault may have any of the following consequences (Zydanowicz, 1979):

- abnormal reduction of the line voltage may result in breakdown of the electrical supply to the consumer.
- when short circuit occurs, an electrical arc is accompanied, and it damages the apparatus within the system.
- other apparatus in the system damaged due to overheating and mechanical forces
- Stability of the system is affected and this may lead to blackout of a given power system.

Types of Faults in Electrical Network: Kaur et al. (2014) categorized power system faults as shunt faults and series faults. The shunt faults can occur as:

(i) Single Line-to-ground fault (SLG): This occurs when one conductor falls to ground or makes contact with neutral wire. It could also be the result of falling trees in a raining storm. (ii) Line-to-Line fault (LL): this resulted when two conductors short-circuited. if a tree branch fall on top of the two of the power lines. (iii) Double Line-to-Ground fault (LLG): This is as a result of a tree falling on two of the power lines. (iv) Balanced three phase fault (LLL): This is a fault occurrence when all the three lines are short circuited. (v) Line-Line-Line-Ground fault (LLLG): This occurs when a tree falls on three power lines. That is, when there is short circuit between three lines and ground in transmission lines. Santamaria (2011) explained series faults as occur along the power lines when one or two lines are broken along the power network which resulted to unbalanced series impedance. This is referred to as 'single phasing' condition in the power system (Gonen, 1987).

1.2 Review of Related Works

As earlier mentioned, several works had been undergone on detection, classification and prediction of electrical faults in power systems. Few among them are reviewed as follows: Jiang et al. (2011) presented a fault discrimination method whose operation is based on negative sequence generated during fault for fast online detection of fault preceded by classification, Support vector machine and adaptive structure neural network was incorporated for efficient operation. However, the computational complexity of the model can be improved. Alqudah et al. (2021) proposed a six-dimensional CNN based model for fault detection in electric grid using big data from multiple phasor measurement units. Its performance was evaluated and compared using classification metric. CNN models outperformed traditional methods. However, it appeared complicated and time consuming due to different stages involved in the process. Fuada et al. (2020) used CNN based model for fault classification on transmission line. The model is simulated using Simulink and MATLAB platform. Machine learning classifier was designed and trained with fault dataset generated. The accuracy of CNN is better when compared with Wavelet feature extraction and ANN. CNN accuracy can be improved due to its computational complexity. Balakrishnan and Gopinath (2020) proposed hybrid of LDA and Cuttlefish optimizer (CFO) technique for detection and classification of line faults in transmission line. LDA was used for feature extraction and CFO based RFA was sed for detection and classification of faults. LDA-CFRFA was executed on MATLAB and implemented on symmetrical and asymmetrical faults. It performance is good but can be improved using appropriate optimizer. Sharmal et al. (2016) presented ANN with wavelet transform for detection and classification of electrical faults on transmission line. ANN of different architectures were tested with statistical attributes of wavelet transform of voltage signal as input features and binary digit as output. Its performance is good but can also be improved with the application of appropriate optimization technique. Pouabe-Eboule and Hassan (2021) proposed Concurrent Neuro Fuzzy technique (CNF) for faults detection and location on electrical transmission line. Fuzzy logic was combined with ANN to detect, classify and locate faults on transmission line. CNF showed high accuracy for both short and long lines in fault classification and location. It can as well be improved on fault detection.

1.3 Research Gap

Application of artificial intelligence and other state of the arts models were being used for diagnosis of

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electrical faults on the power systems. However, their performance can be improved in term of accuracy, efficiency and time response. To achieve this, PMA: a hybrid of MA and POA was done and used to select the optimal parameters of CNN in order improve its complexity requirements and time response. Similarly, the need for optimizer hybridization is to remove shortcoming of MA: Velocity imbalance of female and male mayflies. Therefore, MA is applied to maintain a balance between the exploration and exploitation of MA.

1.4 Contributions

This work has made the following contributions:

- Simulate CNN-PMA using MATLAB 2022a
- Implement CNN-PMA for detection, classification and prediction of faults in SWN electrical network.

II. PROBLEM FORMULATIONS

Here, existing velocity of mayfly is modified to achieve a balance between exploration and exploitation of mayfly algorithm. Existing velocity of MA to be modified is shown in Equation 1 (Zervoudakis and Tsafarakis, 2020).

$$v_{ij}^{t+1} = g * v_{ij}^{t} + a_1 e^{-\beta r_p^2}\left(pbest - x_{ij}^{t}\right) + a_2 e^{-\beta r_g^2}\left(gbest - x_{ij}^{t}\right)$$
(1)

where v_{ij}^{t} is the velocity of mayfly i in dimension $j = 1, \dots \dots n$ at $step\ t$

x_{ij}^{t} is the position of mayfly in dimension j at $step\ t$

β is a fixed visibility coefficient used to limit mayfly visibility to others

r_p is the Cartesian distance between x_i $and\ pbest$

r_g is the Cartesian distance between x_i $and\ gbest$

$a_1\ and\ a_2$ are positive attraction constant used to scale the contribution of the cognitive and social component respectively.

In equation 1, v_{ij}^{t} is the position of a male mayfly, whereas velocity of female mayfly is in Equation 2:

$$v_{ij}^{t+1} = \begin{cases} g * v_{ij}^{t} + a_2 e^{-\beta r_{mf}^2}\left(x_{ij}^{t} - y_{ij}^{t}\right) & if\ f(y_i) > f(x_i) \\ g * v_{ij}^{t} + fl * r & if\ f(y_i) \le f(x_i) \end{cases} \quad (2)$$

$$g = g_{max} - \frac{g_{max} - g_{min}}{iter_{max}}\ x\ iter \quad (3)$$

Where g_{max}, g_{min} are maximum and minimum values that the gravity can take, $iter$ is the current iteration of the algorithm, and $iter_{max}$ is the maximum number of iterations

Female mayfly position varies and only available at the swarm for matting, this affect the performance of the model. In order to improve MA algorithm, its position is modeled after behavior of pelicans during hunting and simulated mathematically as shown in equation 4 and this is substituted for 'v_ij^t' in equation 1 and assumed as modified velocity for both male and female mayfly.

$$x_{i,j}^{P_2} = x_{i,j} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot x_{i,j} \quad (4)$$

Where $x_{i,j}^{p_2}$ is the new status of the i_{th} pelican in the j_{th} dimension based on phase 2, R is a constant which is equal to 0.2, $R \cdot \left(1 - \frac{t}{T}\right)$ is the neighborhood radius of $x_{i,j}$,t is the iteration counter, and T is the maximum number of iterations. $R \cdot \left(1 - \frac{t}{T}\right)$ represents the radius of the neighborhood of the population numbers to search locally near each member to converge to a better solution.

Modified velocity of MA by POA is shown in equation 5

$$v_{ij}^{t+1} = g * v_{ij}^{t} + a_1 e^{-\beta r_p^2}\left[pbest_{ij} - x_{ij}^{p}\right] + a_2 e^{-\beta r_g^2}\left[gbest_j - x_{ij}^{p}\right]$$
(5)

Equation 5 is used to optimize CNN as shown in Flow chart of Figure 1

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Implementation of CNN-PMA Model for Detection and Classification of Faults in SWN

The proposed CNN-PMA is designed and implemented to detect and classify electrical faults in 330kV electrical line in SWN, its flow diagram is shown in Figure 2. The proposed model structures of CNN-PMA for 330kV line is shown in Figure 3. The encoded Gramian angular field (GAF) images of the three voltages and currents for 330kV lines is fed to the three models of CNN- PMA I, CNN-PMA II and CNN-PMA III for detection, classification and prediction of faults respectively. An interactive graphical user interphase (GUI) application is developed with electrical faults on SWN 330kV network data. The GUI is designed using deep learning and optimization toolboxes in MATLAB 2022a. The MATLAB software package is used for the implementation on a computer system with Windows 10 pro: Intel(R) Core (TM) i-5-7300UCPU, 2.7GHz, RAM 8.00GB, 256B SSD, 64-bit Operating System. The total datasets of 276 of electrical faults were obtained from National Control Centre, Osogbo and augmented to 8832 datasets for effective training of CNN-PMA using Equation 6

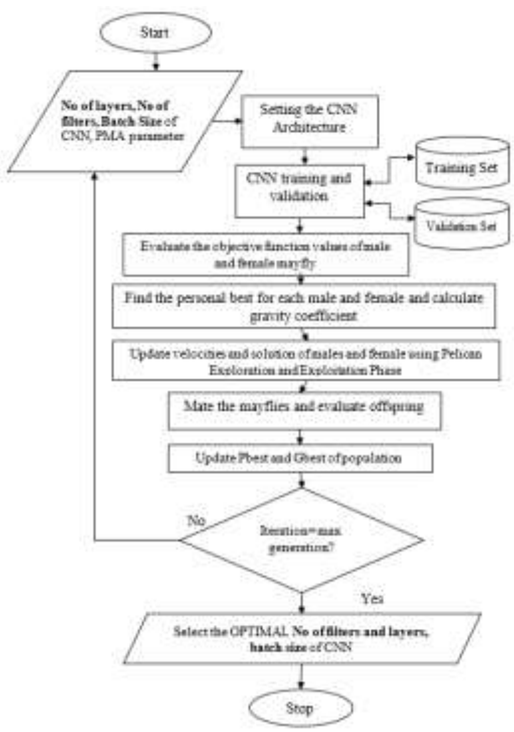

Figure 1 Flowchart of Optimization of Convolutional Neural Network with Pelican Mayfly Algorithm (CNN-PMA)

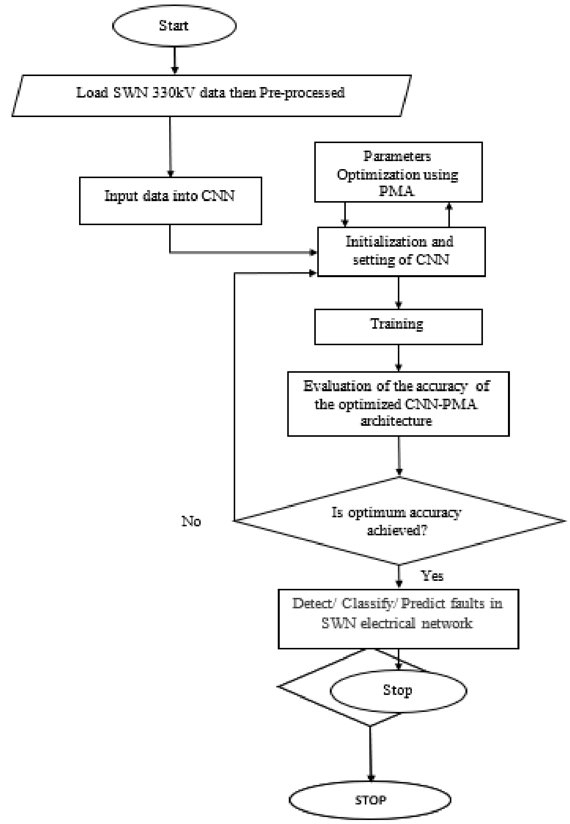

Figure 2 Flow Diagram of Implementation of CNN-PMA Model

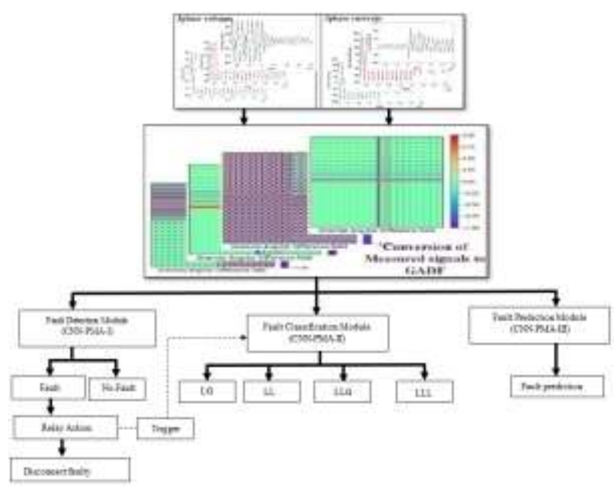

Figure 3 Architecture of the Proposed CNN-PMA Model for SWN 330kV Network

(Shorten et al., 2021). Augmentation was carried-out with the use of three augmentation methods: interpolation, extrapolation, random sampling and the original data (Shorten et al., 2021).

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$$Y = 2^3 \times n \times N \qquad (6)$$

where n is the number of augmentation methods adopted, N is the original number of datasets. Hence, total modelling dataset is: $Y = 2\ 3\ X\ 4\ X\ 276 = 8832$ datasets.

The datasets were employed for training, testing and validation using Random-sampling cross validation technique in the division of 60% : 30%, 70% : 20% and 80% : 10% for training and testing respectively in each case and 10% for validation (Moradzadeh et al., 2022). The developed model was tested and evaluated using the following performance metrics: Mean Absolute Percentage Error, Root Mean Squire Error, Correlation Coefficient, False Positive Rate, Accuracy, Precision and Specification.

III. CASE STUDY

Nigerian electrical power network consists of several generating stations located in remote areas close to the source of primary fuel which are connected to the load centers via long transmission lines. The length of the Nigerian electricity transmission system is about 5,523.8km of 330kV (Ajenikoko et al., 2019). In this work, South-Western Nigeria 330kV network which is around 1,248.6km is considered. A single line diagram of South-Western Nigeria 330kV, 12-Bus system is shown in Figure 4. The entire national grid is sectioned into three geographical zones: North, South-East and South-West. North zone is linked with the south through one triple circuit lines between Jebba and Osogbo, and the South-West is connected to the South-East with the help of one single transmission line from Osogbo to Benin and one double line from Ikeja to Benin (Adepoju et al., 2013).

IV. RESULTS AND DISCUSSION

(i) Results of Faults detection using CNN-PMA on SWN 330kV electrical network.

Tables 1, 2 and 3 showed the detail components of confusion matrixes for CNN, CNN-MA and CNN-PMA respectively. Similarly, Tables 4, 5 and 6 showed the basic components of confusion matrixes for CNN, CNN-MA and CNN-PMA in faults classification for SG, respectively. CNN-PMA possessed lowest numbers of FP and FN (mis-matched) in all the classes of faults considered, this implies that CNN-PMA performed better compared to CNN-MA and CNN, this is because CNN-PMA has higher learning rate due to its high batch-size of 258.

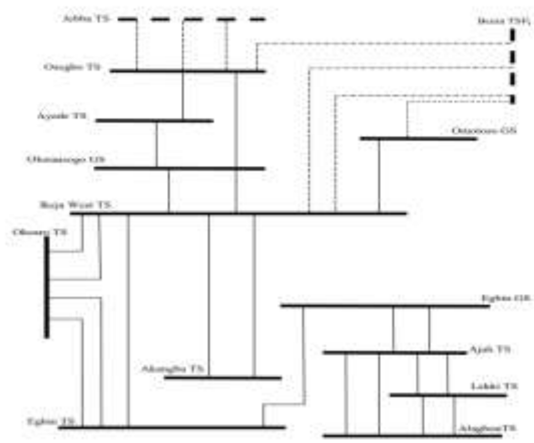

Figure 4 Schematic diagram of SWN 330kV 12-bus network (NCC, 2021).

In addition, Tables 7, 8 and 9 presented different performance evaluation criteria for CNN, CNN-MA and CNN-PMA when employed as classifiers in SG. This showed that performance of CNN-PMA is superior compare to others with highest average values of 98.51%, 98.37% and 98.20% for accuracy, precision and specification, respectively compared to 94.31%, 93.41%, and 95.25% for CNN-MA and 90.87%, 91.56 and 90.20% for CNN, respectively. This resulted from reduction of computational complexity of CNN achieved by PMA optimizer. Furthermore, CNN-PMA has the least values of time response of 31.32seconds and FPR of 1.80%, compared to 46.98seconds and 4.80% for CNN-MA and 66.62seconds and 9.80% for CNN, respectively. Table 10 showed the Comparison of CNN-PMA with other Classifier models in SG

Table 1: Details of confusion matrix components for FC in SG using CNN

Model	Class	Threshold	TP	FN	FP	TN	FPR (%)	SPEC. (%)	PREC. (%)	ACC. (%)	Time (sec)
CNN	REF	0.25	154	13	20	147	11.97605	88.02395	92.21557	90.11976	70.67473
CNN	REF	0.35	153	14	18	149	10.77844	89.22156	91.61677	90.41916	62.33779
CNN	REF	0.45	152	15	16	151	9.580838	90.41916	91.01796	90.71856	63.73403
CNN	REF	0.75	151	16	13	154	7.784431	92.21557	90.41916	91.31737	67.57427
CNN	RSF	0.25	153	14	21	146	12.57485	87.42515	91.61677	89.52096	69.39543
CNN	RSF	0.35	152	15	19	148	11.37725	88.62275	91.01796	89.82036	64.79894
CNN	RSF	0.45	151	16	17	150	10.17964	89.82036	90.41916	90.11976	67.5935
CNN	RSF	0.75	150	17	14	153	8.383234	91.61677	89.82036	90.71856	70.64833
CNN	RWF	0.25	154	13	20	147	11.97605	88.02395	92.21557	90.11976	64.05535
CNN	RWF	0.35	153	14	18	149	10.77844	89.22156	91.61677	90.41916	65.79468
CNN	RWF	0.45	152	15	16	151	9.580838	90.41916	91.01796	90.71856	62.485
CNN	RWF	0.75	151	16	13	154	7.784431	92.21557	90.41916	91.31737	62.78647
CNN	SCF	0.25	155	12	19	148	11.37725	88.62275	92.81437	90.71856	65.43803
CNN	SCF	0.35	154	13	17	150	10.17964	89.82036	92.21557	91.01796	62.68594
CNN	SCF	0.45	153	14	15	152	8.982036	91.01796	91.61677	91.31737	62.95547
CNN	SCF	0.56	152	15	12	155	7.185629	92.81437	91.01796	91.91617	65.75755
CNN	SVF	0.25	156	11	18	149	10.77844	89.22156	93.41317	91.31737	66.788
CNN	SVF	0.35	155	12	16	151	9.580838	90.41916	92.81437	91.61677	64.90534
CNN	SVF	0.45	154	13	14	153	8.383234	91.61677	92.21557	91.91617	66.95936
CNN	SVF	0.75	153	14	11	156	6.586826	93.41317	91.61677	92.51497	65.87241

Table 2: Details of confusion matrix components for FC in SG using CNN-MA

Model	Class	Threshold	TP	FN	FP	TN	FPR (%)	SPEC. (%)	PREC. (%)	ACC. (%)	Time (sec)
CNN-	REF	0.25	15	9	1	15	10.179	89.82036	94.61078	92.2155	46.8850

MA			8		7	0	64			7	9
CNN-MA	REF	0.35	157	10	14	153	8.383234	91.61677	94.01198	92.81437	47.15704
CNN-MA	REF	0.45	156	11	11	156	6.586826	93.41317	93.41317	93.41317	47.2713
CNN-MA	REF	0.75	155	12	9	158	5.389222	94.61078	92.81437	93.71257	47.12506
CNN-MA	RSF	0.25	157	10	18	149	10.77844	89.22156	94.01198	91.61677	47.12631
CNN-MA	RSF	0.35	156	11	15	152	8.982036	91.01796	93.41317	92.21557	47.12029
CNN-MA	RSF	0.45	155	12	12	155	7.185629	92.81437	92.81437	92.81437	47.15942
CNN-MA	RSF	0.75	154	13	10	157	5.988024	94.01198	92.21557	93.11377	46.66674
CNN-MA	RWF	0.25	159	8	16	151	9.580838	90.41916	95.20958	92.81437	47.24572
CNN-MA	RWF	0.35	158	9	13	154	7.784431	92.21557	94.61078	93.41317	47.15468
CNN-MA	RWF	0.45	157	10	10	157	5.988024	94.01198	94.01198	94.01198	47.21853
CNN-MA	RWF	0.75	156	11	8	159	4.790419	95.20958	93.41317	94.31138	46.81707
CNN-MA	SCF	0.25	161	6	14	153	8.383234	91.61677	96.40719	94.01198	47.29235
CNN-MA	SCF	0.35	160	7	11	156	6.586826	93.41317	95.80838	94.61078	47.18163
CNN-MA	SCF	0.45	159	8	8	159	4.790419	95.20958	95.20958	95.20958	46.99157
CNN-MA	SCF	0.75	158	9	6	161	3.592814	96.40719	94.61078	95.50898	47.01946
CNN-MA	SVF	0.25	160	7	15	152	8.982036	91.01796	95.80838	93.41317	46.87071
CNN-MA	SVF	0.35	159	8	12	155	7.185629	92.81437	95.20958	94.01198	47.21119
CNN-MA	SVF	0.45	158	9	9	158	5.389222	94.61078	94.61078	94.61078	46.70849
CNN-MA	SVF	0.75	157	10	7	160	4.191617	95.80838	94.01198	94.91018	47.29056

Table 3: Details of confusion matrix components for FC in SG using CNN-PMA

Model	Class	Threshold	TP	FN	FP	TN	FPR (%)	SPEC. (%)	PREC. (%)	ACC. (%)	Time (sec)
CNN-PMA	REF	0.25	166	1	9	158	5.389222	94.61078	99.4012	97.00599	31.35164
CNN-PMA	REF	0.35	165	2	6	161	3.592814	96.40719	98.8024	97.60479	31.62455
CNN-	REF	0.45	16	3	3	16	1.7964	98.20359	98.20359	98.2035	31.4299

PMA			4			4	07			9	5
CNN-PMA	REF	0.75	163	4	1	166	0.598802	99.4012	97.60479	98.50299	31.48189
CNN-PMA	RSF	0.25	162	5	13	154	7.784431	92.21557	97.00599	94.61078	31.36037
CNN-PMA	RSF	0.35	161	6	10	157	5.988024	94.01198	96.40719	95.20958	31.63475
CNN-PMA	RSF	0.45	160	7	7	160	4.191617	95.80838	95.80838	95.80838	31.61327
CNN-PMA	RSF	0.75	159	8	5	162	2.994012	97.00599	95.20958	96.10778	31.35265
CNN-PMA	RWF	0.25	165	2	10	157	5.988024	94.01198	98.8024	96.40719	31.46602
CNN-PMA	RWF	0.35	164	3	7	160	4.191617	95.80838	98.20359	97.00599	31.37168
CNN-PMA	RWF	0.45	163	4	4	163	2.39521	97.60479	97.60479	97.60479	31.59631
CNN-PMA	RWF	0.75	162	5	2	165	1.197605	98.8024	97.00599	97.90419	31.2972
CNN-PMA	SCF	0.25	164	3	11	156	6.586826	93.41317	98.20359	95.80838	31.64737
CNN-PMA	SCF	0.35	163	4	8	159	4.790419	95.20958	97.60479	96.40719	31.53307
CNN-PMA	SCF	0.45	162	5	5	162	2.994012	97.00599	97.00599	97.00599	31.55497
CNN-PMA	SCF	0.75	161	6	3	164	1.796407	98.20359	96.40719	97.30539	31.52537
CNN-PMA	SVF	0.25	163	4	12	155	7.185629	92.81437	97.60479	95.20958	31.52896
CNN-PMA	SVF	0.35	162	5	9	158	5.389222	94.61078	97.00599	95.80838	31.19175
CNN-PMA	SVF	0.45	161	6	6	161	3.592814	96.40719	96.40719	96.40719	31.6707
CNN-PMA	SVF	0.75	160	7	4	163	2.39521	97.60479	95.80838	96.70659	31.35075

Table 4: Confusion matrix components for CNN model in SG faults classification

Class	Threshold	TP	FN	FP	TN
REF	0.25	154	13	20	147
RSF	0.25	153	14	21	146
RWF	0.25	154	13	20	147
SCF	0.25	155	12	19	148
SVF	0.25	156	11	18	149

Table 5: Confusion matrix components for CNN-MA model in SG faults classification

Class	Threshold	TP	FN	FP	TN
REF	0.25	158	9	17	150
RSF	0.25	157	10	18	149
RWF	0.25	159	8	16	151
SCF	0.25	161	6	14	153
SVF	0.25	160	7	15	152

Table 6: Confusion matrix components for CNN-PMA model in SG faults classification

Class	Threshold	TP	FN	FP	TN
REF	0.25	166	1	9	158
RSF	0.25	162	5	13	154
RWF	0.25	165	2	10	157
SCF	0.25	164	3	11	156
SVF	0.25	163	4	12	155

Table 7: Summary of performance evaluation of CNN model in SG faults classification

Class	FPR (%)	SPEC. (%)	PREC. (%)	ACC. (%)	Time (sec)
REF	10.0134	89.905	91.317	90.613	68.082
RSF	10.628	89.376	90.718	90.045	68.109
RWF	10.029	89.970	91.317	90.643	63.780
SCF	9.431	90.568	91.916	91.242	64.209
SVF	8.832	91.167	92.514	91.814	66.131
Average values	9.786	90.197	91.556	90.871	66.062

Table 8: Summary of performance evaluation of CNN-MA model in SG faults classification

Class	FPR (%)	SPEC. (%)	PREC. (%)	ACC. (%)	Time (sec)
REF	5.389222	94.61078	92.81437	93.71257	47.12506
RSF	5.988024	94.01198	92.21557	93.11377	46.66674
RWF	4.790419	95.20958	93.41317	94.31138	46.81707
SCF	3.592814	96.40719	94.61078	95.50898	47.01946
SVF	4.191617	95.80838	94.01198	94.91018	47.29056
Average values	4.790239	95.20522	93.41345	94.31345	46.98335

Table 9: Summary of performance evaluation of CNN-PMA model in SG faults classification

Class	FPR (%)	SPEC. (%)	PREC. (%)	ACC. (%)	Time (sec)
REF	0.598802	99.4012	99.60479	99.50299	31.2889
RSF	2.994012	97.0599	97.20958	98.10778	31.3565
RWF	1.197605	98.8024	98.80599	98.90419	31.2972
SCF	1.796407	98.2359	98.40719	98.30539	31.5257
SVF	2.39521	97.6479	97.80838	97.70659	31.3575
Average value	1.79601	98.203	98.367	98.508	31.316

Table 10: Comparison of CNN-PMA with other Classifier models in SG

Author	Algorithms	Average Accuracy (%)	Average Precision (%)	Average Recall (%)	Average F-1 score	Time (sec)
Gopinath *et al.* (2016)	SVM	52.93	NA	NA	NA	NA
Sun (2023)	FFNN	52.89	56.04	53.05	57.47	NA
Sun *et al.* (2023)	LSTM	69.42	76.87	64.77	65.58	NA
Sun *et al.* (2023)	CNN	95.18	93.16	90.97	93.03	NA
	CNN	90.87	91.56	90.20	91.29	66.62
	CNN-MA	94.31	93.41	95.05	95.44	46.98

Developed model	CNN-PMA	98.51	98.37	98.20	98.71	31.32

V. CONCLUSION

In order to achieve safe and reliable power system, timely and accurate FDC using CNN and efficient optimisation technique are required. Hence, this work has developed optimised CNN-PMA diagnosis model for the intention of DCP of electrical faults in S-WN electrical networks. PMA was developed by applying Pelican Exploration Model (PEM) to design the attraction process of standard MA as a deterministic procedure instead of random process. Application of PEM established a balance between exploitation and exploration in standard MA. The PMA was used for optimisation of CNN hyper-parameters such as: numbers of convolutional-layer, filters' size in each convolutional-layer, number of convolutional filters and batch-size to develop CNN-PMA model. PMA developed selected optimal parameters of CNN at: 1-layer, 128 number of filters, 6X6 filter size and 256 batch-size.

The faults data of S-WN 330kV electrical network for twenty years were extracted from performance evaluation logbook of NCC, Osogbo and used as modelling data. CNN-PMA was simulated using deep learning and optimisation packages in MATLAB R2020a on computer system with Windows 10 pro: Intel(R) Core (TM)i-5-7300UCPU, 2.7GHz, RAM 8.00GB, 256B SSD, 64-bit Operating System. Datasets obtained were augmented with intention to increase the datasets size to appreciable values for CNN and used for training, testing and validation in the ratio of 70%: 20%: 10%, respectively. Developed CNN-PMA was applied to classify faults on electrical network which consists of TL and SG. Confusion matrix was used to perform processes of fault classification and very good results (TP and TN) were obtained with lowest values of mis-matches compared with CNN-MA and CNN.

Performance of CNN-PMA was evaluated on a standard IEEE 9-bus system using MAPE, RMSE, correlation coefficient, FPR, accuracy, precision and specification. The results obtained showed that CNN-PMA model represented an effective model in faults DCP in S-WN electrical network compared to CNN and CNN-MA and others in its category in terms of MAPE, RMSE, FPR, accuracy, precision specification. Accuracy and speed of CNN-PMA showed its improved performance when compared with other state-of-the-arts methods.

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