ENHANCING CHRONIC KIDNEY DISEASE DIAGNOSIS WITH FPA - DNN

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ABSTRACT

Chronic kidney disease (CKD) is a critical global health concern, requiring accurate and early diagnosis to prevent its progression. Deep Learning (DL)models have shown promise in automating CKD classification from patient data, but the challenge lies in optimizing these models for peak performance. In this study, we propose an advanced approach for CKD classification, introducing the Flower Pollination Algorithm (FPA) for hyperparameter tuning of a Deep Neural Network model. To further enhance model performance, we employ an algorithm known as Oppositional Crow Search (OCS) which is utilized in feature selection and fine-tuning. The integration of FPA and OCS not only optimizes the DNN architecture but also refines the dataset for improved feature relevance. Experimental results demonstrate that the FPA-DNN model, guided by OCS, outperforms other conventional approaches in terms of accuracy, sensitivity, specificity, and F1-score. This research showcases the potential of metaheuristic algorithms in improving DL models for CKD classification and opens avenues for enhanced medical diagnostics through artificial intelligence techniques. The results from the simulations demonstrated high exceptional efficacy for FPA-DNN approach.

Keywords: Internet of Things, Flower Pollination Algorithm, Oppositional Crow Search, Chronic Kidney Disease.

I. INTRODUCTION

In the realm of technology, the Internet of Things (IoT) represents transformative paradigm, enabling seamless connectivity and communication between devices, sensors [1], and systems through the internet. IoT in healthcare enables real-time monitoring and improved patient care. Medical devices collect vital data for personalized treatment, remote patient monitoring, and telemedicine. It addresses the need for efficient, cost-effective healthcare, streamlining processes, reducing errors, and enhancing patient care and accessibility. Deep learning (DL), a subset of AI, excels in healthcare. It trains neural networks to analyses vast clinical data. Using Convolution Neural Network (CNNs) and Recurrent Neural Network (RNNs), DL processes medical images, EHRs, genomic data, aiding disease detection, outcome prediction, and treatment optimization. Its robustness aids faster, accurate decision-making, improving patient care.

Chronic Kidney Disease (CKD) is a prevalent and serious medical condition that demands accurate and timely diagnosis. Deep Learning (DL), particularly Deep Neural Networks (DNNs), shows promise in automating disease classification. To optimize DNNs, this study suggests using the Flower Pollination Algorithm (FPA). FPA is inspired by flower pollination behavior and aids in searching high-dimensional DNN parameters for the best configuration. The study also introduces the Oppositional Crow Search (OCS) algorithm to further enhance optimization. OCS uses opposition-based learning to improve efficiency, enhancing the exploration and exploitation capabilities of the model. By combining FPA and OCS in the context of CKD classification [2], the proposed FPA-DNN model aims to enhance CKD diagnosis accuracy and efficiency. This research contributes to medical diagnostics by integrating advanced optimization algorithms with DL in healthcare.

II. RELATED WORKS

Chen, G et al. [3] introduced an Adaptive Hybridized Deep CNN to efficiently detect and classify kidney disease subtypes, specifically focusing on kidney cancer for early diagnosis. Utilizing DL methods, the AHDCNN model enhances classification accuracy by reducing feature

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dimensions through a CNN-based algorithm. Patil, S et al. [4] employed a model follows a three-phase methodology: pre-processing involving image inpainting and median filtering, followed by feature extraction using various techniques including texture analysis Finally, an optimized deep convolutional neural network is employed for classification, enhancing prediction accuracy through weight and activation function optimization.

Ma, F et al. [5] suggested Heterogeneous Modified Artificial Neural Network (HMANN) as a key element for prompt identification, segmentation, and assessment of kidney failure. The methodology focuses on ultrasound image pre-processing, specifically kidney segmentation, wherein HMANN demonstrates notable accuracy gains and a substantial reduction in contour delineation time. Kriplani et al. [6] utilized 224 records from the UCI CKD dataset and employed a deep neural network to predict the presence or absence of CKD, achieving a high accuracy of 97%. The model was built using cross-validation to prevent over fitting and demonstrated superior performance compared to other algorithms, offering a faster and digitized methodology for accurate prediction of CKD in clinical settings.

Sudharson et al. [7] introduced an ensemble approach that employs pre-trained DNNs, utilizing transfer learning techniques. Three distinct datasets are utilized for feature extraction with pre-trained DNN models (ResNet-101, ShuffleNet, MobileNet-v2), and their ensemble predictions, determined through majority voting, demonstrate superior classification performance compared to individual models. Suresh, et al. [8] introduced artificial neural network algorithms to improve the diagnosis and prognosis of Chronic Kidney Infection. Fourteen distinct properties related to chronic kidney disorder patients were analyzed and utilized to train an Artificial Neural Network.

Devika et al. [9] focused on leveraging ML and data processing techniques to predict CKD. Various data mining and ML classification approaches are explored, including Naive Bayes, K-Nearest Neighbour (KNN), and Random Forest classifier. The study evaluates and compares these algorithms based on accuracy, precision, and execution time, ultimately identifying Random Forest as the superior performer for CKD prediction. Kuo, et al. [10] presented a DL approach employing transfer learning with ResNet model on 4,505 kidney ultrasound images. Data augmentation techniques, kidney length annotations, and bootstrap aggregation were utilized to enhance model performance and reduce over fitting.

Zhang, et al. [11] demonstrated the effectiveness of deep-learning models in identifying CKD and type 2 diabetes using fundus images and clinical metadata. Additionally, the models showcased potential for predicting estimated glomerular filtration rates, blood-glucose levels, and stratifying patients based on disease-progression risk, illustrating the potential of DL for early disease detection and prediction. Bhaskar, et al. [12] presented a novel sensing technique for automated kidney disease detection using salivary urea concentration.

III. METHODOLOGY

The comprehensive method of FPA with DNN is illustrated in Fig. 1. This model presented key steps such as data collection, pre-processing, and feature selection (FS) as its primary components before moving on to the classification stage. The data collection module is designed to gather essential information from Clinical Data Sources (CDS). Furthermore, the gathered data undergoes pre-processing, and the FS steps are employed to improve quality. Subsequently, this methodology is applied for training. For evaluating effectiveness of this approach, we conducted simulations using clinical data in an online mode to assess its ability to correctly classify data into either normal or disease affected.

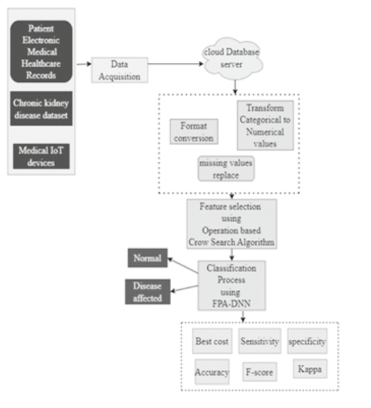

Fig. 1. Proposed model of FPA - DNNA

A. Description of data

At this phase, the suggested system optimizes the acquisition of patient data through IoT devices, gathering information across three distinct data categories. Typically, sensors connected to individuals collect specific medical data over a defined timeframe. In FPA with DNN technique results are examined utilizing well-established, initial data repository consisting of 400 instances and 24 features [14]. To conduct analysis, a 10-fold cross-validation method was employed.

B. Input Pre-processing

Medical dataset may transform to more interpretable form by 3 distinct methods. In the initial step, the input is converted into its original form to simplify subsequent computational processes. Next, listed values in the repository are translated into numerical values, typically represented by zero and one. To conclude, any gaps or lacking values in the repository may filled by replacing them with the median value.

C. FS Model Utilizing OCS

During this stage, the OCS algorithm is applied to select the most optimal set of features from the pre-processed data of CS model developed by Raj et al. [15], which was drawn from the inspiration of the natural hierarchy of crows, specifically their behaviors associated with foraging and food acquisition. This model is built upon the dynamics of a crow flock, including the preservation of food hiding sites, food theft, and mutual tracking. Crows have a certain probability of safeguarding their caches from being pilfered. Fig. 2, depicts the initial and suggested positions of crows (2). To enhance the effectiveness of the CS model, it incorporates a differential method. An opposite operation is initialized for all initial solutions, and through comparisons, optimal one is selected as the best solution. The implementation of the model is given in coming section.

During the community initialization phase, crow community is assigned using F_i, and the initialized features of crows are distributed haphazardly within a designated search region.

$$F_i = F_1, F_2, \ldots . . F_n \; where \; i = 1,2,3, \ldots, n \qquad (1)$$

Typically, the optimization techniques begin with original values that are then iteratively improved. A comparison of these values results in the selection of perfect one for the original value. To illustrate, let's take an example where we have a real number represented as $f \in (g,h)$. Using the definition of an opposite point, we can express it as follows

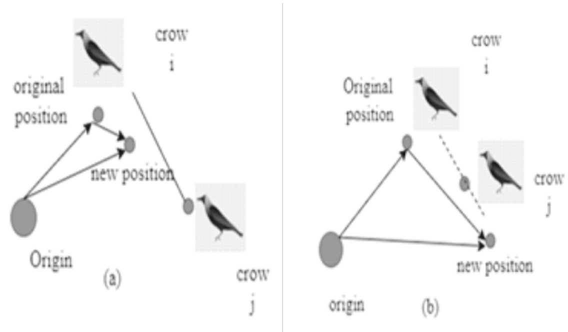

Fig. 2. Universal technique of CS

$$\underline{f}_j = g_j + h_j - f_j \qquad (2)$$

In the OCS approach, the Fitness Function (FF) is defined based on the objective function, with the primary goal being the identification of the most favorable features within the database images being used in the model.

$$O F_i = MAX(Accuracy) \qquad (3)$$

A crow generates next location through random selection from a group of crows, with each crow *'j'*. A crow intervenes location, denoted as P^i, at iteration *iter,* is determined using the provided Eq. (4).

$$P^{i,iter+1} = \{ P^{i,iter} + r_i \times A^{i,iter} \times \left(mem^{j,iter} - P^{i,iter} \right) if \, r_j \geq A \qquad (4)$$

Where, $r_i \& r_j$ are randomly selected values for crows & *j,* respectively, ranging among zero and one. Flight length of crow i is $A^{i,iter}$ at iteration *iter,* location of crow *P,* memory location is indicated by mend, and $AP^{j,iter}$ signifies effective probability of crow *j* at that particular iteration. The most recent updates to the crow's location as well as memory special attributes are enhanced through the utilization of Eq. (5).

$$mem^{i,iter+1} = \{ P^{i,iter} f \left(P^{j,iter+1} \right) > f \left(mem^{j,iter} \right) mem^{i,iter} \; Otherwise \; f(5)$$

The new position of the crow exhibits a significantly high fitness value within the designated location. By adopting this new position, the crow enhances its memory. Upon reaching the maximum iteration limit, the optimal memory position closely coincides with the objective. This technique is represented in Fig. 3, for a visual representation of the process.

D. Classification based on DNN

DL techniques extract high-dimensional features from input databases, which enhance classifier performance, especially when integrated with autoencoders (AE) and Support Vector Mechanism (SVM) classifiers [16]. AE's primary goal is generating appropriate codes to represent input vectors. The associations between the input and output of an encoder are described as $c = g_E\ (W,b;\ u)$ and are represented by Eq. (6).

$$c=f\left(b+W^{Z}u\right)(6) \qquad (9)$$

The activation function of an encoded neuron is represented by 'f'. Connections between the input of the hidden layer and the b vector, representing neuron bias, are established by W weight of the encoding unit. The u vector corresponds to the input of the encoder section, while the vector c signifies the output of the encoding unit. This relationship is illustrated in (7).

Fig. 3. OCS Flow chart

$$\hat{u}=\hat{f}\left(\hat{b}+\widehat{w}_c\right) \qquad (7)$$

Within this model the activation function is denoted as $\hat{f}$. Outcome of the autoencoder $\hat{u}=g_{AE}\left(W,b,\widehat{W},\hat{b},u\right)$. Its objective function is given by,

$$E_{sparse}=E_z+\beta\sum_{q=1}^{N}\square\, KL\text{¿} \qquad (8)$$

The predefined cost function consists of two components. Initially, EZ represents the objective function of the Neural Network (NN), while sparsity weight is β.

$$E_z=\frac{1}{2}\sum_{k=1}^{z}\square\, e_k^2+\frac{\lambda}{2}\left(\|W\|+\|\widehat{W}\|\right) \qquad (9)$$

Regularization unit λ, a critical component employed to address and mitigate overfitting concerns. Error vectors can be defined by discrepancies among the intended outcomes and real outcomes, as demonstrated here.

$$e_k=\|u^{(k)}-\hat{u}\| \qquad (10)$$

In this scenario, where k takes on values from 1 to Z, it's noteworthy to recognize that EZ represents the internal weight of the Autoencoder (AE), where,

$$E_z=E_{AE}\text{¿} \qquad (11)$$

$$KL\left(\rho\,\|\,\hat{\rho}_q\right)=\rho log\frac{\rho}{\hat{\rho}_q}+\left(1-\rho\right)\log\frac{1-\rho}{1-\hat{\rho}_q}(12)$$

$$\hat{p}_j=\frac{1}{Z}\sum_{p=1}^{z}\square\, f_q\left(u^{(i)}\right) \qquad (13)$$

Here, ρ represents the desired sparsity value, and ρ ̂ is defined as follows:

A Stacked Autoencoder (SAE) system is created by interconnecting the components of the Autoencoders (Aes). The SAE is formed by multiple AEs interconnected within the encoder. AE with L-cascaded, is illustrated as.

$$g_{SAE}=g_E^1\, o\, g_E^2\, o\ldots\ldots o\, g_E^L$$
$$(14)$$

E.Tuning utilizing FPA

Within the Flower Pollination Algorithm (FPA) [17], the concept of pollination mirrors the principles of plant reproduction. A scalable approach to address specific optimization challenges is provided by flower and pollen gametes. The most effective and dependable solution is identified as flower constancy. In global pollination, pollinators transfer pollen over long distances to reach more suitable destinations, while local pollination occurs within smaller regions, targeting unique flowers in shaded areas. Global pollination introduces the concept of a "switch probability," where the replacement of a stage triggers local pollination. FPA incorporates four general rules, as outlined below.

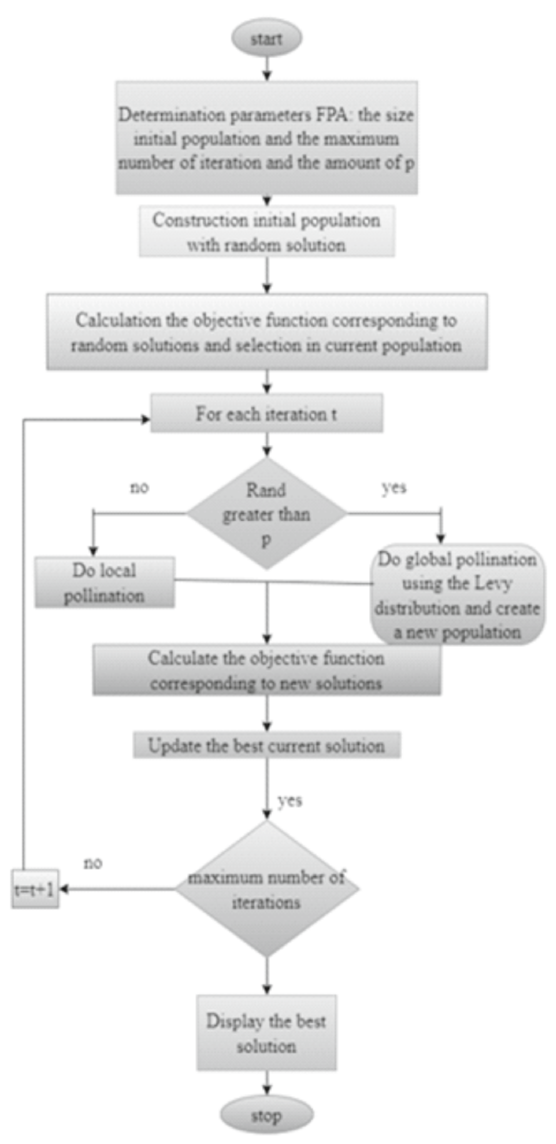

Fig. 4. FPA flowchart

● The Levy flight method is employed by pollen pollinators in global pollination, encompassing live and cross-pollination.

● Abiotic and self-pollination are included in local pollination.

● The pollinators that foster flower fidelity are recognized as insects.

● The regulation of the interplay is done with probability of a switch. As such, the 1st and 3rd rules can be described as follows.

Here, at iteration t, x_p^t signifies the pollen vector, while $g_{¿}$ represents the most recent optimal solution. A scaling factor, $\gamma = a$, thus Levy's distribution, is represented by L [18]. Furthermore, L corresponds to a Levy distribution, as depicted below.

$$L \quad \frac{\lambda \times \Gamma(\lambda) \times \sin\frac{\pi\lambda}{2}}{\pi} \times \frac{1}{S^1+\lambda} S \geqslant S_o 0 \qquad (16)$$

Regarding to local pollination, both the 2nd and 3rd rules are implemented, as detailed below: - (λ) denotes a standard gamma function.

$$x_p^{t+1} = x_p^t + \varepsilon\left(x_q^t - x_k^t\right) \qquad (17)$$

Here, x_q^t and x_k^t, pollens from distinct flowers of the same plant are represented.

In numerical terms, when , x_q^t and x_k^t which are originate from the same plant and are chosen from a comparable community, this phenomenon is termed a 'local random walk'. Here, ε is generated from a uniform distribution ranging between [0, 1]. Fig. 4, provides an illustration of the workflow of the Flower Pollination Algorithm (FPA).

IV. RESULTS AND DISCUSSION

To guarantee the effectiveness of the FPA-DNN model, it is imperative to apply the model extensively across various domains. The following sections delve into the repository, feature values, as well as achieved results. The assessment of simulation results is based on a range of diverse evaluation parameters.

A. Evaluation of Result

Outcomes from the analysis of the OCS with FS technique were evaluated against existing FS models based on their optimal cost performance. The selected features are presented in Table I and depicted in Figure 5. The table values indicate that less effective FS performance was observed with the CFS algorithm, where the highest optimal cost of 0.79 was achieved. In comparison, a moderate FS performance was displayed by the PCA model, with an optimal cost of 0.4570. While reasonable optimal costs were achieved by the PSO-GS and GA-FS models, specifically 0.03656 and 0.03440, the optimal cost of 0.00986 was achieved by the OCS-FS model. Additionally, it is evident that a set of 12 features out of the original 24 was selected by the OCS-FS algorithm, namely features 2, 4, 5, 8, 10, 12, 13, 14, 16, 19, 20, and 22.

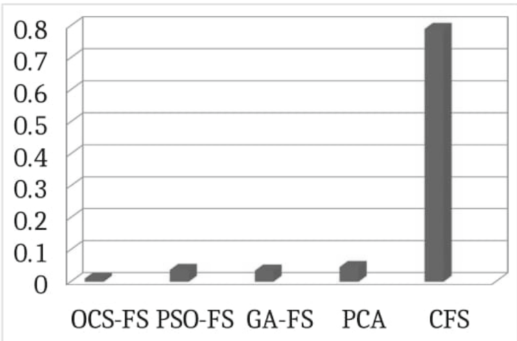

Fig. 5 Evaluation of suggested model with others based on cost performance

In Fig. 6, the confusion matrix from the execution of the FPA with DNN technique is presented. A total of 248 instances were categorized as positive, and 147 instances were categorized as negative by the FPA with DNN technique.

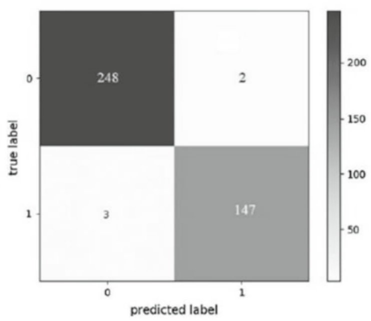

Fig. 6 FPA-DNN confusion matrix

TABLE I. EVALUATION OF FS METHODS FOR CKD DATASET

Methods	Best cost	Selected features
OCS-FS	0.00985	2, 4, 5, 8, 10, 12, 13, 14, 16, 19, 20, 22
PSO-FS	0.03658	15, 12, 24, 23, 13, 20, 11, 8, 18, 3, 9, 1, 14, 5, 2, 6, 17, 19
GA-FS	0.03441	16, 24, 13, 9, 14, 17, 22, 19, 2, 15, 23, 18, 12, 6, 4, 10, 3, 20
PCA	0.04572	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18
CFS	0.79001	4, 6, 7, 10, 15, 17, 19, 22

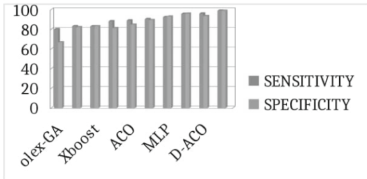

Fig. 7 Evaluation based on sensitivity and specificity

An evaluation of sensitivity and specificity of suggested technique with existing [19–21] is depicted in Fig. 7. The figure highlights that subpar performance in diagnosis was shown by the Olex-GA approach, with a minimum value for sensitivity and specificity. In contrast, improved results were demonstrated by the LR technology. A moderate sensitivity and specificity values were exhibited by the XGBoost approach, both at 83.01%. Notable results were yielded by the PSO technology, with a sensitivity of 88.05% and a specificity of 81%. Reasonable results were demonstrated by the DT framework, with a sensitivity of 90.37% and a specificity of 89.26%. A slightly moderate performance was displayed by the MLP technology, with a sensitivity of 92.32% and a specificity of 92.84%. On the other hand, the least favorable outcomes were shown by the FNC method, with a sensitivity of 95.66% and a specificity of 95.88%. Furthermore, competent results were produced by the D-ACO scheme, boasting a sensitivity of 96.01% and a specificity of 93.32%. Lastly, superior performance was exhibited by the FPA-DNN framework, attaining the highest sensitivity of 98.82% and specificity of 98.67%.

In Fig. 8, the analysis of our suggested technology with existing techniques in terms of F-score as well as kappa is depicted. It shows that inadequate diagnostics, a minimum F-score and kappa is demonstrated by the LR approach. Moderate values were exhibited by the XGBoost and

OlexGA technique. In alignment with this, a considerable outcome was generated by the PSO model. Subsequently, a superior outcome was achieved by the ACO scheme. Furthermore, satisfactory results were demonstrated by the DT framework. Following this, slightly enhanced results were exhibited by the MLP scheme. Furthermore, slightly superior results were obtained by the D-ACO method. Competitive results were showcased by the FNC model. Finally, all other methods were surpassed by the FPA-DNN model, achieving the maximum F-score of 99.01% and a kappa of 97.32%.

Evaluation of accuracy for suggested methodology compared to existing methods are presented in Fig.9. Figure demonstrates that the achieving the lowest accuracy of 75.05%, Olex-GA technique performs poorly in diagnostics, but better accuracies are gained by LR and XGBoost techniques. Following this, moderate accuracy values was achieved by PSO and ACO techniques. Furthermore, near-optimal performance accuracy was obtained by the D-ACO and FNC approaches. Ultimately, the FPA with DNN technique achieves 98.74% which is an exceptional excellent accuracy.

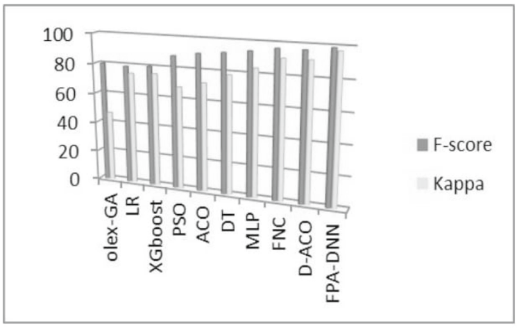

Fig. 8 Evaluation based on F-score and kappa

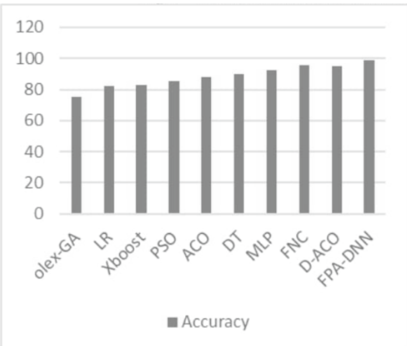

Fig. 9 Evaluation based on Accuracy

V. CONCLUSION

The research article introduces an innovative CKD diagnosis model, known as the FPA-DNN model, which is IoT and cloud-based in design. This model involves several key stages, including data collection, pre-processing, FS, and classification. Initially, patient health information is collected using IoT devices. The FPA with DNN model leverages the algorithm of OCS to perform FS, identifying a prime selection of features from the pre-processed input. By applying the FPA algorithm, further fine-tunes the DNN parameters, resulting in improved grouping accuracy. Experimental evaluation of the FPA with DNN technique was done on a benchmark of input dataset, confirmed its superiority. It achieved the highest sensitivity at 98.82%, specificity at 98.67%, accuracy at 98.74%, F-score at 99.01%, and kappa at 97.32%. Looking ahead, the performance of the FPA-DNN model can be further enhanced through the implementation of clustering and outlier removal techniques.

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