Intelligent Health Assessment Based on Communication and AI Technologies for Public Health

Anupa Sinha[1], Yalakala Dinesh Kumar[2]

[1]*Associate Professor, Department of Information Technology, Amity University Rajasthan, Jaipur, Rajasthan, India. Email: doctorrakhimutha4@gmail.com*

[2]*Research Scholar, Department of CS & IT, Kalinga University, Raipur, India*

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ABSTRACT

Automating EEG pattern categorization in public health helps in the early detection of epilepsy and other brain illnesses. However, present methods have difficulties in reaching excellent accuracy and adaptability. This study utilizes a hybrid strategy that incorporates Spider wasp-tuned Convolutional neural network (SW-CNN). Convolutional neural networks (CNNs) use complex feature extraction from EEG data, and Spider wasp optimization (SWO) improves network parameters by comparing them to the pursuing and developing behaviors of spider wasps. By enhancing classification accuracy, precision, recall, and F1-score measures, the combined effect seeks to achieve significant improvements over conventional techniques. The research concludes that the SW-CNN hybrid model performs better at differentiating between non-seizure activity and epileptic seizures. This strategy improves diagnosis accuracy and efficiency in public health, resulting in better patient outcomes and treatment planning. Effective transmission of such results is critical for furthering clinical diagnosis and research in neurological diseases.

1. Introduction

The incorporation of new technology in public health increases the efficiency of real-time data collection and its evaluation, which has a profound impact on the delivery of health care. Thus, the identified periodicity, as well as fluctuations, can be used in the early stage of the disease, the development of personalized therapy, and the effective use of resources [1]. The adoption of technology proclaims significant improvements in the quality and quantity of health in areas where resources such as medical practitioners, equipment, and facilities are scarce [3]. Such advancement helps reduce the existing disparities in the healthcare delivery systems since they promote disease-preventive measures and have an impact on the accessibility of public healthcare services [2]. Through improved communication, the usage of these technologies can improve the public health care system as a whole and lead to more equitable, better, and appropriate treatment for everybody. In general, the use of these technologies has the knowledge effect of bringing the public healthcare system as a whole into providing more appropriate, better, and equal treatment [4]. It also serves to ensure that all population groups can get quality health care and at the same time increases the quality of the services being offered. The continual advancement of these technologies presents a great opportunity to increase the impact and accessibility of public health initiatives, and hence, the health of the society as a whole [6]. The objective of this study is to improve EEG data processing by combining SWO with CNN, thereby enhancing the automated diagnosis of epilepsy and other brain diseases [5].

Related works

The significance of such innovations in tackling global health issues was emphasized by the research [8]. The handling of the situation, improved customer communication, comprehension of the COVID-19 spread, along with the acceleration of research and treatment were all made possible by ML and AI. Considering the obstacles, authorities need to establish confidence in those advances to address health issues and accomplish equitable growth objectives linked to optimum wellness and health. In [10] looked at how public health and digital technologies may be used to combat the COVID-19 epidemic. According to the analysis, big data, AI, 5G, and cloud computing were the most effective technologies for slowing COVID-19 spread. Vulnerabilities, data latency, fragmentation, and privacy security were among the difficulties encountered. The study emphasized how crucial it was to include digital technology in public health [11]. The usage of AI in healthcare settings as well as the significance of medical communication for the results of patients and healthcare professionals were covered in [12].

AI coding's validity and dependability, its use for interaction training and auditing, and its limits were all covered. AI has been used in training for abilities to communicate, audit, provide feedback, and create inclusive training through the use of models. An IoT-based methodology for tracking pupil wellness was presented in [14] to track pupils' vital signs over time and identify behavioral and biological changes. The system examined data using ML techniques, and the support vector machine (SVM) produced the best results, with an accuracy of 99.1%. The model performed better than multilayer perceptron neural networks, random forest, and decision tree techniques [7].

2. Methodology

Dataset

The dataset [15] used in this research consists of EEG recordings from 500 participants, divided into 5 categories based on the brain activity observed during 23.6 sec sessions. The recordings of each participant are sampled into four thousand and ninety eight data points, which are then separated into thirty-three categories, each of which has hundred and seventy eight data points that represent one second's worth of EEG data. The collection of data aims to classify EEG patterns into 5 segments: 1 for seizure activity, and 2-5 for various non-seizure conditions such as recording from tumor locations, and healthy brain areas with eyes open or closed [9].

Enhancing CNN Parameter using SWO

SWO algorithm replicates female spider wasps' natural hunting, nesting, and mating habits. Female spider wasps use unique nesting and hunting activities to find prey (spiders) and nests for placing eggs. SWO deposits one egg in the midsection of each spider, simulating hunting, nesting, and seeking activities as well as the obligatory brood parasitism for certain wasp species. The following equations may be used to represent each female spider-wasp in the SWO as a solution for the present generation in the D-dimension vector:

$$\overrightarrow{SW} = [w_1, w_2, w_3, \dots, w_C] \tag{1}$$

The following describes the original spider wasp community (of size M),

$$SW_{Pop} = \begin{bmatrix} SW_{1,1} & SW_{1,2} & \cdots & SW_{1,C} \\ SW_{2,1} & SW_{2,2} & \cdots & SW_{2,C} \\ \vdots & \vdots & \vdots & \vdots \\ SW_{M,1} & SW_{M,2} & \cdots & SW_{M,C} \end{bmatrix} \tag{2}$$

To produce any solution arbitrarily in searching space, use this equation,

$$\overrightarrow{SW_j^s} = \vec{K} + \vec{q} \times (\vec{G} - \vec{K}) \tag{3}$$

Exploration stage (Searching): To identify the spider that will be best for their progeny, the female wasp in this stage roves the search area at random. Here is how this behavior may be represented mathematically,

$$\overrightarrow{SW_j^{s+1}} = \overrightarrow{SW_j^s} + \mu_1 * (\overrightarrow{SW_b^s} - \overrightarrow{SW_a^s}) \tag{4}$$

where the female wasps come first and two arbitrary indices, b, and a, define the direction of investigation; μ_1 is then used to calculate the continuous mobility across the present path using the equation that follows,

$$\mu_1 = |q_m| * q_1 \tag{5}$$

where q_1 is a number that is randomly created between one and zero, and q_m is an arbitrary number that is generated following a normal distribution. When a female wasp drops a spider from an orb, they can lose it and search the region around the exact spot where the fragment is located. The subsequent model of mathematics may be used to represent this behavior,

$$\overrightarrow{SW}_j^{s+1} = \overrightarrow{SW}_d^s + \mu_2 * \left(\vec{K} + \overrightarrow{q_2} * \left(\vec{G} - \vec{K}\right)\right), \mu_2 = A * cos(2\pi k),\ A = \frac{1}{1+f^k} \quad (6)$$

Here$d$ is an indicator that randomly selects from the sample and k is a number that is arbitrarily produced between 1 and -2. A compromise between Equations (4) and (6) is suggested to boost research and identify the most interesting regions. In [0, 1], there are two random numbers, $q_3 and q_4$.

$$\overrightarrow{SW}_j^{s+1} = \begin{cases} Eq.(4) q_3 < q_4 \\ Eq.(6) Otherwise \end{cases} \quad (7)$$

Exploration and exploitation stage (Following and escaping): The wasp begins following the prey (spider) when it has located it. Here is how this behavior may be represented logically,

$$\overrightarrow{SW}_j^{s+1} = \overrightarrow{SW}_j^s + D * \left|2 * \overrightarrow{q_5} * \overrightarrow{SW}_b^s - \overrightarrow{SW}_j^s\right| \quad (8)$$

$$D = \left(2 - 2 * \left(\frac{s}{s_{max}}\right)\right) * q_6 \quad (9)$$

A random integer in the range [0, 1] and a vector demonstrating values arbitrarily provided in the range [0, 1] are represented by q_6 *and* q_5, respectively. The value of b is chosen randomly from the sample. Wasp speed is controlled by a distance factor called D, which begins at 2 and decreases linearly to 0. This stage is the beginning phase of exploitation. As the gap evolved, exploitation turned into exploration. With the following equation, one may imitate this behavior.

$$\overrightarrow{SW}_j^{s+1} = \overrightarrow{SW}_j^s * \overrightarrow{ud} \quad (10)$$

A vector created by the normal distribution between l and $-l$ is called $\overrightarrow{ud}$. To progressively widen the gap between the female wasp and the spider, l is therefore created using Eq. (11).

$$l == 1 - 1 * \left(\frac{s}{s_{max}}\right) \quad (11)$$

According to the following equation, the compromise between both trends is arbitrarily determined,

$$\overrightarrow{SW}_j^{s+1} = \begin{cases} Eq.(10) q_3 < q_4 \\ Eq.(12)\ \ Otherwise \end{cases} \quad (12)$$

Nesting exploitation (behavior): At this point, the immobilized spider is being pulled into a nest by the female wasp. Due to the variety of nesting activities shown by spider wasps, these habits are replicated in the SWO method using two distinct equations. To construct the ideal nest to place the immobilized spider and deposit an egg across its abdomen, the initial equation involves dragging the spider into the area with the most suited spider. The explanation of the initial equation is as follows,

$$\overrightarrow{SW}_j^{s+1} = \overrightarrow{SW^*} + \cos(2\pi k) * \left(\overrightarrow{SW^*} - \overrightarrow{SW}_j^s\right) \quad (13)$$

There are many other ways that spider wasps create their nests. These include hollows left by fallen leaves or rocks, mud nests made by the wasps in the ground, and pre-existing nests like beetle holes or spider (prey) nests. The following formula is suggested to prevent creating two nests in the same location,

$$\overrightarrow{SW}_j^{s+1} = \overrightarrow{SW}_j^s + q_3 * |\gamma| * \left(\overrightarrow{SW}_b^s - \overrightarrow{SW}_j^s\right) + (1 - q_3) * \vec{V} * \left(\overrightarrow{SW}_a^s - \overrightarrow{SW}_d^s\right) \quad (14)$$

The numbers $q_3, b, a,$ and$d$ are the identifiers of three answers that were arbiter chosen from the individuals; γ is a number derived based on the levy flight and the binary vector $\vec{V}$ is employed to ascertain the appropriate step size to prevent the construction of 2 nests at the exact position. The following formula determines$\vec{V}$'s assignment. A flowchart of the nesting and hunting behaviors in SWO is shown in Figure 1.

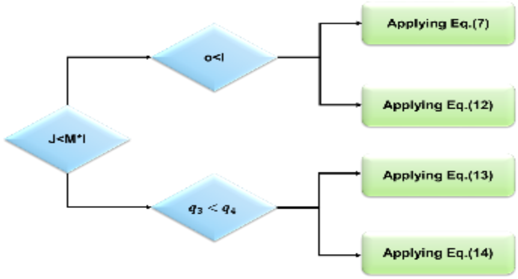

Figure 1. Flowchart of the nesting and hunting behaviors

Convolutional Neural Networks for EEG Pattern Classification

CNNs are employed in a variety of domains, including computer vision and signal processing, because of their ability to extract hierarchical characteristics from input automatically [13]. A convolutional, max-pooling and fully-connected neural network architecture is a CNN. The one-dimensional double CNN has four convolutional layers that represent complicated aspects of the input space. A repaired linear unit (ReLU) activation function is applied to pooling layers using the characteristics gathered from these layers. The volume will be $[q, r]$ depending on the number of kernels. Several kernels in this case are represented by R. Kernels (filters) are used to determine the feature maps. In the k + 1th convolutional layer's lth map of features for the $w_{j,i}^{k}$space of input, the value of feature$y_{j,i,l}^{k+1}$ at the position (j, i) is computed as follows,

$$y_{j,i,l}^{k+1} = \omega_l^{k^S} . y_{j,i}^{k} + a_l^{k} \tag{15}$$

Where the bias component of the kth filter of the kth layer is known as a_l^k, and the vector weight is represented by k= 1 and $y_{j,i}^{k} = w_{j,and\ i}^{k}$are the values of the first layer. The kernel creates the feature map $y_{j,i,l}^{k+1}$. The first layer's output is subjected to the second convolutional process. In contrast to multi-layer networks, CNN uses the activation function to convert data in a non-linear way to identify non-linear properties. The transformation of (16) is done using the non-linear activation function to achieve this goal.

$$b_{j,i,l}^{k+1} = a(y_{j,i,l}^{k+1}) \tag{16}$$

Where the equation (15) is used to determine $y_{j,i,l}^{k+1}$. Tanh, sigmoid, and ReLU are examples of common functions that activate. The paper makes use of the ReLU non-saturated activation function. The symbol for it is $max(0, y_{j,i,l}^{k+1})$. A convolutional layer's feature map is transformed into a pooling layer's feature map. The output of the pooling layer for each feature map $b_{j,\mathrm{I},l}^{k+1}$ is ascertained by:

$$y_{j,i,l}^{k+1} = pool\left(y_{n,m,l}^{k+1}\right), \forall (n, m) \in Q_{j,i} \tag{17}$$

The model employs convolutional, ReLU, and pooling operations to obtain a feature map. Multiple convolutions, pooling layers, and ReLU are used to determine more descriptive characteristics. Each of the neurons in the layer before it is linked to all of the neurons in the present layer across the integrated layer. The output of a fully connected network is clustering results.

$$z_j^{(k)} = e\left(y_j^{(k)}\right) with\ y_j^{(k)} = \sum_{j=1}^{n_j^{(k-1)}} \omega_{j,i}^{(k)} z_j^{(k-1)} \tag{18}$$

Where e is a function of transfer demonstrated by the non-linearity and $\omega_{j,i}^{(k)}$ are the completely linked layers' weight coefficients that link the neurons. After identifying the output signals, the CNN begins to be trained. The CNN's output contains the loss function, which is calculated during training. The network's interconnections are altered by propagating this loss function backward. The decrease in the loss function serves as the basis for updating the network's connections.

$$\theta_i = \theta_i - \epsilon \frac{\nabla_\theta K(\theta)}{\sqrt{h_{s+1}} + 1f^{-5}}; \quad h_{s+1} = \alpha . h_s + (1-\alpha)\nabla_\theta K(\theta)^2 \tag{19}$$

Where $K(\theta) = \frac{1}{M}\sum_{j=1}^{M} k(\theta; zc^{(j)}, z^{(j)})$the function of loss is computed at the network's output;~ is the learning rate; α is the decay rate; zc and z are the desired and present values of the network output; and N is thenumber of training pairs. CNN parameters are established during the training phase.

Spider wasp tuned Convolutional neural network (SW-CNN)

SW-CNN combines bio inspired algorithms that mimic spider wasps' hunting and nesting to increase diagnostic precision for public health in communication-focused applications. Through enhancing the CNN architecture based on SWO adaptive search and optimization, the approach of SW-CNN leads to a better classification of EEG patterns and thus a faster diagnosis of epilepsy and other brain disorders. By integrating these biological strategies within an automated medical image analysis framework, such an approach strives to implement reliable healthcare solutions in communication-oriented public health.

3. Results and discussion

Our method was created in Python (version 3.11) on Windows 10. The system can handle challenging machine-learning tasks since it has a powerful high-performance graphics card and an Intel Core i5 CPU. By employing a range of measures such as accuracy, recall, precision, and f1-score, the effectiveness of the suggested method (SW-CNN) may be examined. These metrics were contrasted with currently used techniques like Logistic Regression (LR) [16], Random Forest (RF) [16], and Deep Learning (DL) [16].

Accuracy: The precise feature of the SW-CNN model established through the evaluation and classification of the tasks reveals high efficiency over conventional approaches. Comparing SW-CNN with LR at 80%, RF at 85% and DL at 90%, which relatively produced lower accuracy rates, SW-CNN stood out to produce 96% accuracy, as shown in Figure 2. Determines general accuracy in classifying health data in communication-oriented public health, which is imperative in assessing the correctness of the diagnosis.

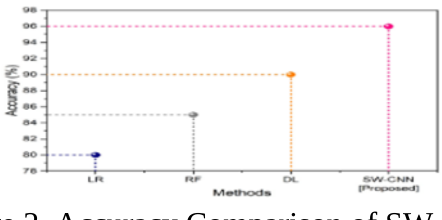

Figure 2. Accuracy Comparison of SW-CNN

Precision: Moreover, the achieved level of high differentiation in the SW-CNN model highlights its ability to solve the fine-grained classification problem in comparison with the other approaches. Shows the percentage of correct predictions of the positive instances, which is important in the public health screen to reduce false positive results. The proposed SW-CNN was found to be less accurate than LR (75%), RF (80%), and DL (85%), but had a remarkably higher precision of 91%, as outlined in Figure 3.

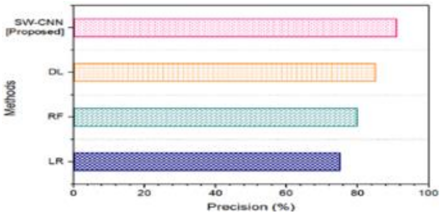

Figure 3. Precision Comparison of SW-CNN

Recall: As shown in Figure 4 below, SW-CNN outperformed LR (85%), RF (90%), and DL (95%) by having a high recall rate of 97%. While traditional approaches can fail in such requirements, the high recall of the SW-CNN model proves useful in tasks demanding sensitive detection. Filters work to prevent overloading the model and to increase the ability to detect true positives, this is crucial for communication-oriented public health and for accurately identifying a patient's overall state of health.

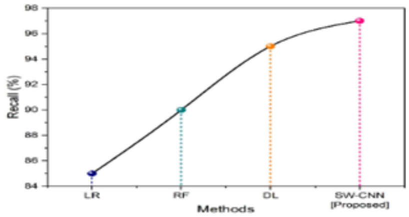

Figure 4. Recall Comparison of SW-CNN

F1-score: Figure 5 presents SW-CNN in comparison to LR with 80%, RF with 85%, and DL with 90% outperformed by SW-CNN with an F1-score of 93%. The balances between precision and recall are so crucial in the evaluation of communication-oriented public health data. Analyzing the results in terms of F1-score, it can be emphasized that the SW-CNN model achieves much higher performance over the conventional methods, making it more reliable and accurate.

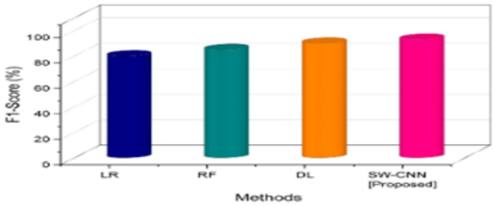

Figure 5. F1-score Comparison of SW-CNN

4. Conclusion and future scope

Concerning the application of the concepts of machine learning on EEG data, the potential future benefits of automatically categorizing EEG patterns in public health contexts are significant in the early diagnosis of epilepsy and other brain illnesses. This study presents a novel category of a sensing technique that employs the SW-CNN. CNNs also outcompete the other in complex features identification in EEG data while SWO improves the other network properties in the manner of spider wasps hunting and nests. High rates of increase in other metrics such as accuracy (96%), precision (91%), recall (97%), and F1-score (93%) constitute the goal of this type of hybrid model in comparison to conventional methods. Addressing computational complexity and dataset heterogeneity is crucial for equitable communication-oriented public health interventions. Future work includes validating the technique on larger clinical datasets and diverse patient demographics to confirm its robustness

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