Predicting Neurological Disorders Linked to Oral Cavity Manifestations Using an IoMT-Based Optimized Neural Networks

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ABSTRACT Anatomically, oral cavity and central nervous system have a close relationship; the mouth and face are the location for 30-40% of the body's sensory and motor nerves. The identification of orofacial manifestations of neurological disorders is usually in direct relation with the responsibilities of a dental surgeon. Therefore, familiarizing dental surgeons with theses manifestations is essential to have better recognition, diagnosis, and correct decisions upon treating their associated Neurological Disorders. These manifestations should be efficiently analyzed using novel effective techniques since their related neurological disorders need to be early identified to avoid serious consequences. Furthermore, preventive dental care for patients with neurological disorders and all kind of rehabilitative treatments necessitates well-planned and effective novel approaches. The Internet of Medical Thing (IoMT) is a relatively new technology that allows the transfer of medical data over a secure network of medical sensors and wearable devices. The data transferred are of utmost importance in diseases diagnosis and treatment. In this paper, an IoMT-based Intelligent Guided Particle Local Search with Optimized Neural Networks (IGPLONN) approach is proposed. Firstly, dental data are collected from the International Collaboration on Cancer Reporting (ICCR) oral cavity and central nervous system. Secondly, features are extracted from data and IGPLONN algorithm is utilized to select the effective features by minimizing the feature dimension that helps improve the overall prediction rate. Finally, the obtained features are transferred to the central health application through the IoMT platform where they can be analyzed by dental practitioners for neurological disorders prediction. The hybrid optimized technique improves the overall oral-linked neurological diseases detection rate. Moreover, it efficiently manages the forecast parameters that are used to predict the dental metastasis with minimum computational complexity. The performance of the proposed system has been experimentally evaluated on MATLAB to verify its excellence. The results revealed that proposed IoMT-based IGPLONN method attains the maximum accuracy of 98.3% compared to other methods.

INDEX TERMS Oral cavity, neurological disorder, central nervous system, intelligent guided particle local search algorithm, neural network, Internet of Medical Things (IoMT).

I. INTRODUCTION

Internet of Things (IoT) refers to the connections of different devices around the world to transfer, process, and store the data [1], [2]. IoT has different applications in different fields. But now, with the invasion of the advanced cutting-edge technology, Internet of Medical Things (IoMT), studies are showing that the inflammation found in periodontal may play a more specific role in causing or increasing the risk for certain medical conditions [3]. IoMT has revolutionized health

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care sector drastically since last decade [4], [5]. As shown in figure 1, IoMT is a combination of medical sensors and wearable devices that can connect to health care storage systems via networking technologies allowing the transfer of medical data over a secure network [6]. A specialized form of IoMT is Internet of Dental Things (IoDT) which is an innovative approach to achieve prevention and management of dental caries, periodontal diseases, oral cancers, and other dental diseases. IoDT could play vital role in collection and monitoring of patients' data for oral health care; moreover, this data could be used in eventual risk assessment and further research [7].
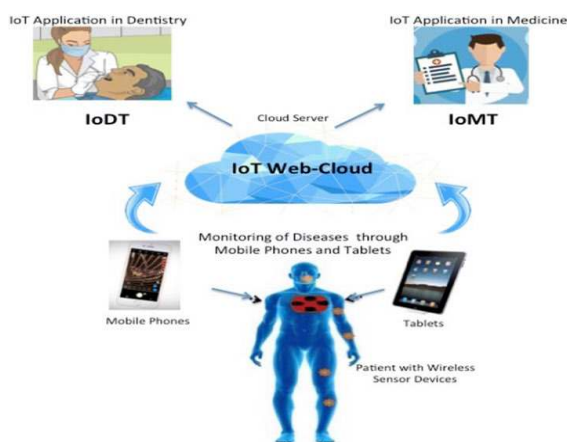

FIGURE 1. **IoMT and IoDT [7].**

For years, healthcare professionals suspected there was a link between oral infections and some medical conditions, but they thought this was because bacteria from the mouth made its way to other parts of the body. Recent research has shown that the central nervous system and oral cavity have a close anatomical location [3], [8]–[11]. It has also shown a strong relationship between gum disease and many mental health problems, including stress, depression, distress, anxiety, and loneliness [12]. Therefore, dentists should be familiarized with those common diseases between neurology and dentistry. The potential overlap of neurological symptoms over dental manifestations should be thoroughly explored as unawareness with them may lead to serious consequences [3], [9]. For example, the common neurocutaneous diseases include tuberous sclerosis, and neurofibromatosis of von Recklinghausen and incontinentia pigmenti have significant direct relationship to oral cavity and orofacial structures. Moreover, oral environment may also be severely altered the neoplasias of orofacial nerves and their sheaths, cranial nerve tumors with orofacial affections, and systemic tumors with significant neural and orofacial symptoms [3]. The orofacial nerves and orofacial affections may lead to several nervous problems and create neurological disorders.

Among the several neurological diseases, Parkinson's disease is the one with the most challengeable neurological problem which is caused by improper dental management [10]. This mention dental process linked with the tongue check

lip control, muscle eye coordination, and digital dexterity, which directly affect the brain function and central nervous system. The dental manifestations associated with central nervous system disorders have been analyzed according to several case studies to get insights on the dental-neurological relationship [11]. One study [11] was concerning a 38 years old lady who did not have any significant medical symptoms while checking their dental status, but she felt some pain in her left-hand side since the past 3 weeks. The pain transferred to her left sided hand and face creating severe headache. Then, this pain spread all over the body in 2 years and created left and right leg pain. Due to the severe pain, the patient was continuously examined for her family history but the result was negative. Finally, a dental examination was carried out to determine the oral manifestation [13] that might had affected several regions such as left trigeminal nerve, cranial nerve and left supra orbital region. The diagnosed dental infections and the orofacial manifestations were linked to the demyelinating lesion in brain which was proved by the Magnetic Resonance Imaging (MRI).

Along with this, one of the dangerous neurological diseases called neurofibromatosis [14], which is created by the mutation of the NF1 gene which has been analyzed using IoMT sensor as shown in the figure 2 with blue and red patches. These patches which indicate the sensor data movement to the brain nerve have been analyzed with 50 ms interval based on the response curve. It is one of the genetic disorders which affect one child in every 3000 children. Recently, the NF1 type of disease is spread mostly due to the tongue lesion, macroglossia diffuse and fungiform papillae enlargement. As discussed earlier, neurofibromatosis is a genetic disease, however, once a patient is affected by orofacial manifestations [15] such as dental abnormalities; jaw bone problem, cranial lesion, teeth impacts, overgrowth of alveolar and teeth supernumerary, the risk factors of neurofibromatosis disorders increases. To conclude, orofacial manifestations of the neurological diseases fairly exhibit a coherent and reasonable association of these diseases with dentistry. We believe for the personalization of dental care for each patient with
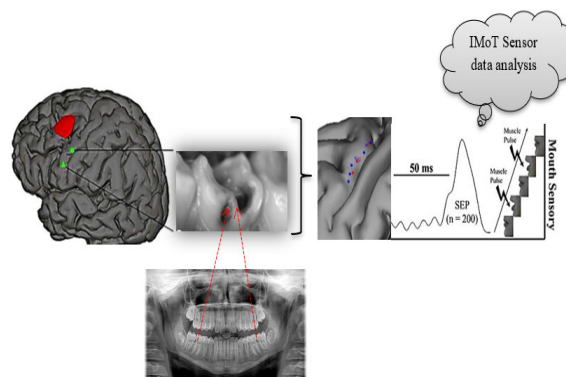

FIGURE 2. **Structural Connectivity Flow of central nervous system and oral cavity on IoMT platform [14].**

neurological diseases. Once the patient is affected by the oral cavity manifestations [16], [17], physical examination in clinic and the respective central nervous system should be investigated using brain imaging and signal recording. The collected medical information should then be analyzed using novel effective techniques since neurological disorders related to oral cavity manifestations need to be identified early to avoid serious consequences.

From the above discussion, it can be clearly shown the strong relationship between dental disease and many neurological disorders, therefore, dentists should be able to identify orofacial manifestations of neurological disorders efficiently. To achieve this goal, we propose an IoMT-based Intelligent Guided Particle Local Search with Optimized Neural Networks (IGPLONN) approach. Firstly, dental data are collected from the International Collaboration on Cancer Reporting (ICCR) oral cavity and central nervous system. Secondly, features are extracted from data and IGPLONN algorithm is utilized to select the effective features by minimizing the feature dimension that helps improve the overall prediction rate. Finally, the obtained features are transferred to the central health application through the IoMT platform where they can be analyzed by dental professionals for neurological disorders prediction. The hybrid optimized technique improves the overall oral-linked neurological diseases detection rate. The performance of the proposed system has been experimentally evaluated on MATLAB to verify its excellence. The results revealed that proposed IoMT-based IOGPLSNN method attains the maximum accuracy of 98.3% compared to other methods such as Genetic optimized back propagation neural network (GABPNN) [42], Particle swarm optimized radial basis function network (PSO-RBNN) [43] and Bee colony optimized convolution neural network (BCCNN) [44].

The rest of this paper is organized as follows: section 2 reviews the work related to our research problem. Section 3 introduces the proposed IoMT-based Intelligent Guided Particle Local Search with Optimized Neural Networks (IGPLONN) approach. Section 4 evaluates the excellence of the proposed algorithm and in section 5, we give our conclusion remarks and future work direction.

II. RELATED WORKS

For this purpose, different researcher concentrates their work in the dental field to predict the oral disease in an earlier stage. Sabrina Wiemann *et al.*, [18] were analyzing the oral health and hygiene to predict the various diseases from German people using clustering techniques. Initially, effective questionnaires are created, which is asked to the patient for collecting the dental information. The created set consists of 484 questionnaires, which being examined in terms of applying the oral hygiene impact profile factor 14, and similar information are grouped using clustering techniques. In this work, [18] k-means and ward's clustering techniques are used to group, which helps to predict 96 rare diseases effectively. From the predicted diseases, most of the diseases are being

created due to oral malocclusions, abnormal teeth development, teeth changes, and dysgnathia. At last, the excellence of the system is assessed using numerical results and analysis in which the earlier oral health detection process minimizes the impact of other disease affection in people's health effectively based on IoMT platform.

Mignogna M.D. *et al.*, [19] were examining the link between oral health and other diseases such as chronic disease, neurological disease, musculoskeletal disorders, Endocrine disorders, Localized diseases, respiratory disease, renal disease, cardiovascular disease, and psychiatric disease. During the analyze oral process part are evaluated in terms of systemically because oral nervousness is linked with other parts of the body. Hence, the examined details are correlated with other disease symptoms to get knowledge about the interface between oral health and other diseases in the human body. From the analysis, different diseases, diagnostic procedures, and treatment methodologies are provided to improve the clinical decision-making process successfully. Saccucci *et al.* [20] were diagnosing oral cavity related autoimmune disease using clinical analysis. First, the dental information is collected with the help of dentists, which are fed into autoimmune pathologies to get the knowledge of the disease. Once the disease is detected, manifestation related disease is detected, treatment procedures are provided to minimize the difficulties in patient health effectively on IoMT platform.

Laura *et al.* [21] were predicting oral caries related chronic disease by applying artificial neural networks. During this process, 189 demographic details are collected, which are examined continuously to get the relationship between each information and subjects. The subjects are examined to get knowledge about caries, restoration information, teeth loss, and other details. The gathered teeth information is processed using a neural network with a relevant diagnosis tool to classify the subjects into normal and chronic disease affected people. Then the efficiency of the system is assessed using numerical analysis in which the introduced neural network-based system ensures 0.69% of accuracy, 0.75% of the area under curve value. Lalithamani *et al.* [22] were detecting oral cancer by applying the deep neural adaptive fuzzy systems. The method collects patient information from dentists, which is examined using defined fuzzy logic. The fuzzy approach analyses each information and group similar information into a separate cluster, which is done with the help of fuzzy c-means clustering. Then the clustered dental data is processed, and the cancer details are obtained using a deep neural network approach that gets the knowledge from the previous analysis. The effective analysis of patient detail interrelationship helps to predict oral cancer successfully. The excellence of the system is assessed using numerical results, and the system achieves 96.29% of accuracy while classifying oral cancer.

In the light of aforementioned work, oral hygiene and dental health management play an important role in human health since they are fundamental sources for several rare diseases.

So, researchers have been utilizing effective prediction techniques and clinical diagnosis to understand the relationship between the oral health and other diseases such as chronic diseases, respiratory disease, neurological diseases, cardiovascular diseases, etc. which is discussed in [19]. Among the several discovered relations, the relation between oral cavity manifestations and neurological diseases is the most complicated, confusing and dangerous since it completely affects the central nervous system. This relation should be efficiently analyzed and well-understood using novel effective techniques in order to be able to early identify the underlined neurological disorders and avoid their serious consequences.

Yin *et al.* [42] proposed the Genetic Algorithm optimized Backpropagation Neural Network (GABPNN) for optimization of the injection molding process parameter. A BPNN model was established to determine the mathematical association between the optimization goals and process variables. GA was employed to optimize the process variable that would outcome in the optimal solution of the optimization objectives. Melt temperature, mold temperature, packing time, packing pressure, along with the cooling time, are measured to be a design parameter.

Hu *et al.* [43] introduced the particle swarm optimization with a radial basis function neural network (PSO-RBFNN) for regional logistics demand prediction. The PSO-RBFNN model is used to fit well the nonlinear correlation between the regional logistics demand and the regional economy. RBFNN topology enhances the learning speed and prevents the local minimum. Beside, RBFNN's transfer function assumes radial basis functions, specifically the Gaussian function. As the Gaussian function has a modest depiction, and multivariable input could not add many intricacies.

Banharnsakun *et al.* [44] introduced the Bee colony convolutional neural network (BCCNN). The findings of the experiment reveal that both precisions of detection and computation time can be increased by the approach suggested. A distributed bee colony algorithm for enhancing the performance of CNN for deep leaning. The proposed BCCNN method is utilized to determine the optimal initialization weight set to be employed in the CNN training process.

Harnale and Maktedar [45] suggested the Support Vector Machine classifier for oral cancer detection. An effective algorithm for detecting lesions in the early phases and achieving high precision is the Hybrid Approach to KFCM segmentation. Feature extraction using first-order, second-order statistics, and SVM classifier for normal lesion and abnormal lesion classification.

Dima *et al.* [46] proposed a Decision Tree approach (DT) to determine the impact of oral health on dental care. The top-down C4.5 algorithm was used to build a classifying inductive decision tree. The C4.5 DT study was used to identify the main factors that affect the occurrence of dental cavities for infants. The parental designation, deteriorating, absent, and filled permanent teeth (DMFT), periodontal examination results, and periodontal pocket depth was established as the designation factor for the caries of infants. DT established parental health classifications.

Romeo *et al.* [47] discussed the Naïve Bayes and K–nearest neighbor (KNN) for predicting tumor grade and nodal status in oropharyngeal and oral cavity squamous cell carcinoma. K-Nearest Neighbor (KNN) is an instance classifier that assigns the Euclidean linear distance to a label for each object, taking into consideration K-nearest neighboring elements.

In this paper, IoMT- based Intelligent Guided Particle Local Search with Optimized Neural Networks (IGPLONN) approach for oral cavity linked neurological disorders prediction is proposed. IoMT-based IGPLONN provides an effective prediction technique to determine the oral cavity related brain disease successfully. The hybrid optimized technique helps reduce the computation complexity, improves the overall disease, and the oral cavity linked nervous problem detection rate. For this advantage, the system uses the intelligent guided particle local search algorithm with neural networks to predict the oral cavity linked neurological problem. Moreover, the proposed system is used to manage the parameters that used to predict the dental metastasis in a reliable manner, which minimizes the system complexity. IoMT for dental treatment focuses mainly on preventive maintenance approaches by recognizing the source of oral health issues at the earliest time and sharing data with the dentist and the patient around the clock. Smart toothbrushes may be used to collect patient knowledge on their brushing practices. Such toothbrushes come with a variety of innovations such as cameras, motion sensors, and many more. The built-in camera in the brush is used to monitor brushing activity.

III. THE IoMT-BASED IGPLONN APPROACH
In this section, we present and analyze the proposed IoMT-based IGPLONN system for oral cavity linked neurological disorders prediction. During the analysis process, the system utilizes the International Collaboration on Cancer Reporting (ICCR) oral cavity and central nervous system dataset (http://www.iccr-cancer.org/datasets/published-datasets/head-neck/carcinomas-of-the-oral-cavity-tnm8) [23]. The dataset was created in the year of 2011; it consists of several organ details. The oral cavity and central nervous system data were used to predict the link between the oral cavity and neurological disorders [24]. The oral cavity data was collected from tobacco habit patients as well as a normal patient since the causes of the cavity are varied. Based on this information, brain function and changes were recorded in the dataset used in this work. As discussed earlier, the dataset consists of several teeth information that was captured according to the chemotherapy, radiotherapy, immunotherapy, and targeted therapy processes [25]. The procedures are varied from one patient to another; procedures are applied to the dental process that successfully recognize the oral cavities from lip, tongue, hard palate, mouth floor, gingiva, retro-molar trigone, buccal vestibule, alveolar process, maxilla, mandible and other areas which are shown in figure 3 [26].
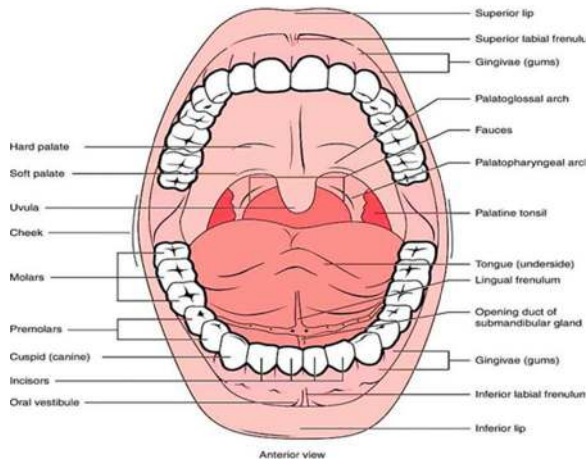
FIGURE 3. Structure of Oral Cavity [26].

The location of affected area, infection nerves, tumors, and other details were collected in different directions such as left, right, upper, and midline. In addition, teeth fungal infection, inflammation, Proliferative verrucous leukoplakia, and HPV positive dysplasia details [27] were gathered from the patients. These details were collected from 10000 patients and are used to predict the link between the oral cavity and neurological disorders. This process is done with the help of IGPLONN algorithm; the working process is demonstrated in figure 4. The utilized effective algorithm chooses an effective feature by minimizing the feature dimension that helps improve the overall prediction rate.

As shown in figure 4, the oral cavity linked neurological problem detection system comprises several steps such as data collection from ICCR dataset, dental feature derivation, selection of optimized dental information, and recognition of oral cavity linked nervous problem using IoMT. Patient treatment is growing increasingly mobile-oriented and IoMT platforms are important in allowing patients to be in control
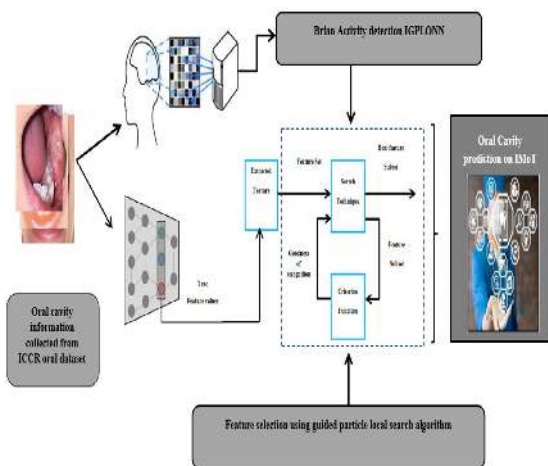
of their own health while easily exchanging these details with their dental practitioners. With the help of smartphone apps, Bluetooth-enabled Toothbrush records someone's brushing relevant data to study the person's dental health and share statistics with the dentist. Nowadays, IoDT plays an important role in information gathering, analysis with respect to dental data and monitoring the status of patients in oral health care. These capabilities effectively utilize the objective function that is used to manage the parameters reliability to improve the overall performance of oral linked nervous problem detection. The detailed working steps are described in the following sections (3.1 to 3.3).

A. ICCR DATA COLLECTION AND NORMALIZATION ON IoMT PLATFORM

Initially, oral cavity data are gathered by preparing a questionnaire which includes dental information, oral cavity details, nerve information, and other brain-related information. The collected information [28] is stored in the dataset for each patient, which also includes several inconsistent data filled by the patient him/herself that reduces the overall prediction accuracy. Due to the manual and physical examination process, few data might be missed from the list. The missing values [29] are identified and replaced or removed from the list to improve the overall prediction accuracy. The replacement value is achieved by computing the average of the entire values present in a particular column or row in the list. Few data need to be normalized for enhancing the appearance or quality of the data. Oral cavity data processing elements in an IoMT platform are shown in the Figure 5. The normalization process converts the input range from -1 to 1, which is done by applying the coefficient variance normalization process [30]. The method estimates the distribution of the data in the list according to the mean and standard deviation value based on activation function represented as $\sum f$. This introduced method successfully understands the context of data in the list; it minimizes the number of data instead of computing the standard deviation; the system computes the coefficient value. The normalization process is performed using Eqn (1).
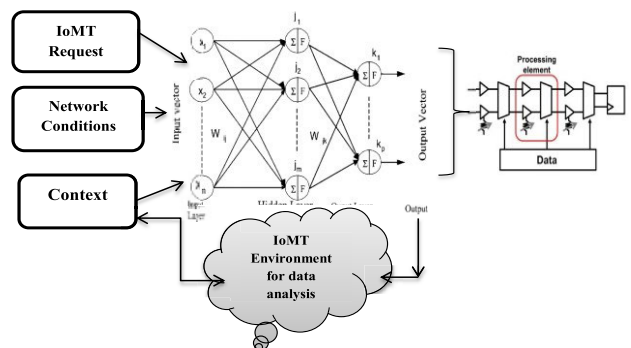
$$y' = \frac{\sigma}{\mu} \} \ based \ on \ w_{ij} \qquad (1)$$

FIGURE 4. Oral cavity linked neurological problem detection system architecture.

FIGURE 5. IoMT data processing element.

where y' denotes oral cavity normalized features, σ represents the standard deviation of values in column or row, and μ is mean value.

During this computation process, exponential distribution value [31] is computed to get the importance of data in the list. The distribution is computed as follows,

$$f\left(x = (X_1. \ldots .X_n; \lambda)\right) = \begin{cases} \lambda e^{-\lambda k_1 \ldots k_p} & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (2)$$

where x is denotes a particular input from the list, $\lambda = \{\lambda k_1 \ldots .k_p\}$, it is the rate parameter of distribution ($\lambda > 0$). Based on this process, the importance of data is identified to minimize the representation of oral cavity data effectively. After that, various features [32] derived from the list, which includes the entropy, average, correlation, maximum, minimum, probability, standard deviation information are extracted. The extracted features are maintained to get the knowledge about the oral cavity linked nervous problem is identified. The extracted features are huge in dimension, which needs to be reduced to improve the overall interface recognition process; this is done using intelligent guided particle local search algorithms.

B. FEATURE SELECTION USING INTELLIGENT GUIDED PARTICLE LOCAL SEARCH ALGORITHM

The most important step of this work is selecting optimized features [33], [34] from the feature set since few extracted features are overfitting to the search space. Some of the features are unwanted to recognize the oral cavity linked nervous problem that must be removed from the feature space for improving the disease recognition rate. Due to these reasons, an intelligent guided particle local search algorithm is used in this work to select the best feature from the feature set. The introduced method is an effective Meta heuristic approach [35] that effectively changes the feature searching criteria. During the feature searching process, penalties are generated to minimize the local search problem since it produces an optimal local solution. The introduced method effectively picks the optimized features due to the successful utilization of objective function [36]. Initially, the features are arranged in the feature space for getting the optimal solution since each feature has various characteristics. After that, the feature similarity computation is avoided since the employed algorithm detects the optimal features in a global manner, not in a local manner. Hence, the cost function co_i is defined for every feature fe_i, along with cost, feature penalty pe_i is also defined. Initially, the penalty value must be 0, which used to determine the number of occurrences of features in local minima. Using the feature and respective cost function, an objective function is determined to select the global feature from the feature set. In addition to this, indicator function If_i is defined to measure whether the selected features belong to the current solution or not (1 or 0). During this computation process, feature penalty value is local minima value, and the feature values are increased according to

the maximum utility that is computed as follows,

$$util\,(x, i) = If_i \frac{c_{oi}(x)}{1 + pe_i} \quad (3)$$

Along with the utility value, candidate solution need to be computed to get the optimal solution from the solution list which is estimated as follows,

$$gls\,(s) = g\,(s) + \lambda * \sum_{i=1} \left(pe_i * If_i(s)\right) \quad (4)$$

In Eqn (4), $gls\,(s)$ represents a candidate solution for the given oral cavity feature set, λ denotes the global search parameter and i is a feature set for having the penalty value. Along with the features, maximum utility and candidate solution, position, and velocity [37] of a feature need to be examined to determine the optimal features. The computed feature position and velocity value need to be updated using the following Eqn (5 and 6).

$$v\,[i] = v\,[i] + c1 * rand\,(i) * (pbest\,[i] - present\,[i])$$
$$+ c2 * rand\,(i) * (gbest\,[i] - present\,[i]) \quad (5)$$
$$present\,[i] = present\,[i] + v\,[i] \quad (6)$$

In Eqn (5) v[i] denotes the feature velocity, present [i] denotes the current solution rand () having the random number from 0 to 1. Learning values are denoted as c1 and c2 (c1=c2=2). After that, the computed candidate solutions are arranged in the search space, which is further analyzed using an objective function that is computed from feature value and penalty value multiplication process. Once the extracted features satisfy the above computation, which is having a maximum value that is treated as the optimal solution used for further oral cavity linked neurological disease detection process. According to the discussion, the pseudo-code of intelligent guided particle local search algorithm is depicted in table 1.

Based on the above algorithm, the optimized oral cavity linked nervous problem features are selected from the feature set. The selected features are processed by an optimized neural network that successfully recognizes whether the selected oral cavity features are caused to brain disease or not. The detailed classification process is discussed in the following section 2.3.

C. ORAL CAVITY LINKED NEUROLOGICAL DISORDERS IDENTIFICATION USING AN OPTIMIZED NEURAL NETWORK

The final step in the proposed approach is to classify the oral cavity linked neurological disorders using an optimized neural network. During the recognition process, the network [38] effectively utilizes the selected oral cavity features, which is examined using different layers of the network. The network has several layers, such as convolution, ReLu layer, pooling, loss, and drop out layer. These layers are successfully evaluating the oral features using a particular function that identifies the link between oral features and brain disease features. During this process, the system utilizes the back propagation network [39] used for feature training process

TABLE 1. Intelligent guided particle local search algorithm pseudo code.

> *Initialize:* $fe_i, If_i, co_i, gls(s), \lambda, k, pe_i$ *and* M
> *Begin*
> $0 \leftarrow pe_i$
> *For Start every feature* $i \leftarrow$ *until* M *do*
> *Define objective function for every feature*
> $$gls(s) = g(s) + \lambda * \sum_{i=1} (pe_i * If_i(s))$$
> *While Perform to reach stopping condition*
>
> *Begin*
> *For* $i \leftarrow$ *until* M *do*
> *Estimate feature utility*
> $$util(x, i) = If_i \frac{c_{oi}(x)}{1 + pe_i}$$
> *Then compute the penalty of each feature*
> *For each feature i computed until to reach maximum feature utility do*
> $$pe_i \leftarrow pe_i + 1$$
> $$k \leftarrow k + 1$$
> *End process*
> *Update position and velocity of each feature in feature set.*
> *Compute penalty of feature and continue the above process*
> *Select the optimized features according to the objective function*
> *Return Selected feature.*

that used is to minimize the deviation from the expected and computed oral cavity features. The representation of training is depicted in figure 6.
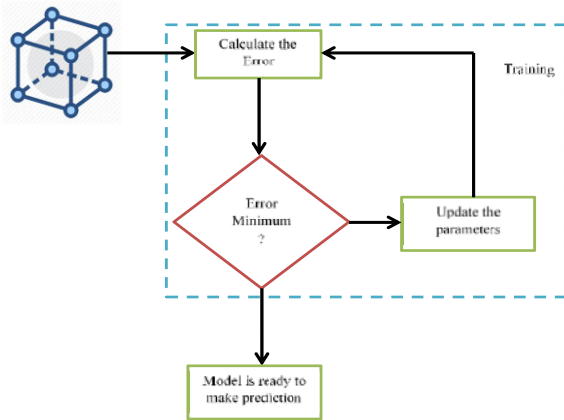

FIGURE 6. Representation of feature training.

The feature training process is optimized with the help of auction process since it minimizes the complexity exist in the oral cavity classification process as well as minimizing the oral feature training time. The auction process assigns each feature into specific nodes exist in the network that effectively resolve the assignment problem while performing the feature training process.

As inferred from the figure 7, the rectified linear unit utilizes the activation function since it maps the input oral cavity features into the output process. The activation function is computed as follows,

$$f(x = \{x_1 \ldots \ldots x_i\}) = (1 + e^x)^{-1} \qquad (7)$$

Based on the activation function, the output is estimated, in which the system may produce an error value, which should be reduced for improving the overall recognition rate. The error is minimized in the pooling layer because it successfully uses the lp_boosting approach [40]. The boosting approach minimizes the variance present in the network that is computed as follows,

$$f(x) = \sum_{j=1}^{J} \alpha_j h_j(x) \qquad (8)$$

In Eqn (8), α_j denotes the non-negative weak features present in pooling layer, h_j represents the best features in the provided feature set. After performing the training process, the features are applied to the drop out layer to predict the status of the oral cavity feature. The testing features are analyzed in the network layer, and the output is computed using network weight and specific input value which is done as follows,

$$y_{in} = \sum_{i=1}^{n} x_i w_{ij} \qquad (9)$$

In Eqn (9), yin is represented as the output value of particular input, x_i is specific input, and $w_{ij} = \{Bias\ analysis\}$ is represented as the weighted value of particular input. As discussed earlier in the training process, the error value is minimized by the replacement of updated weight value that is computed as follows,

$$w_{ij}(new) = w_{ij}(old) + x_i y_j \qquad (10)$$

Finally, the income feature status is determined according to the following function

$$y_j = \{o_1 \ldots o_k = f(y_{in}) = \begin{cases} -1 & if\ y_{in} > 0 \\ 0 & if\ y_{in} = 0 \\ +1 & if\ y_{in} < 0 \end{cases} \qquad (11)$$

From the computed value, if the incoming feature has 0 values, then it belongs to the normal oral cavity feature based on error analysis. If the estimated output is maximum to 0 value, that is denoted as oral cavity features belongs to the neurological diseases-related features otherwise the feature treated as normal oral cavity features based on the labels and annotation. The efficiency of the system is calculated utilizing numerical analysis that determines the prediction accuracy of the oral cavity linked neurological diseases.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section deals with the excellence of the proposed oral cavity linked neurological diseases prediction system. At the time of the process, the system collects the oral cavity details from ICCR oral cavity dataset [41] that collects patient information according to the developed questionnaires. In this paper, a statistics t-test has been performed
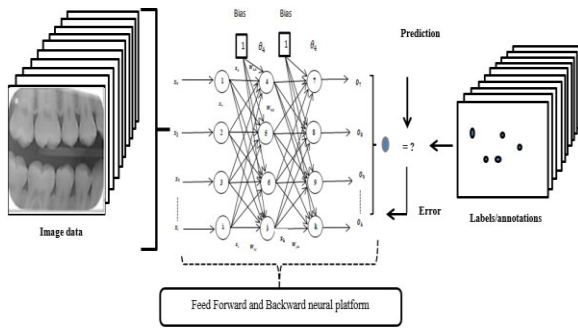
FIGURE 7. Neural analysis for image data analysis.

with standard benchmark methods for effective experimental results. The proposed IoMT-based intelligent guided particle local search algorithm with optimized neural network (IGPLONN) was executed on dental images, which can effectively and quickly recognize the tooth diseases, this offers the diagnostic basis for dentists and saves treatment time. The collected patient details are analyzed using an intelligent guided particle local search algorithm with an optimized neural network for predicting the oral cavity linked brain problems. The proposed system was developed using the MATLAB tool, in which 70% of data used as training data and the remaining 30% of data used as testing data with experimental analysis as shown in the Figure 8. In both data (training and testing), the created system perfectly classifies the features depending on the objective function and training process.
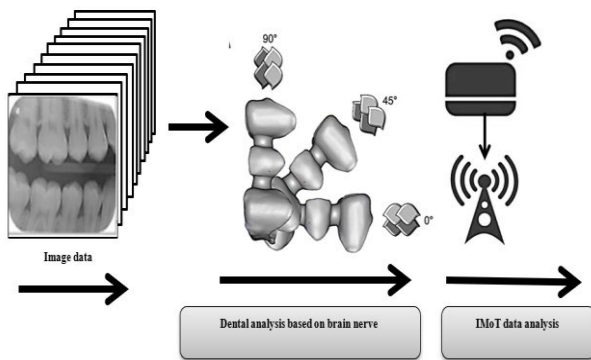

FIGURE 8. Analysis for dental image data based on IoMT.

A. ERROR RATE

The successful selection of oral cavity features and lp boosting training process reduces the deviation between the selected and computed features. This deviation is determined using the error rate value, and the obtained result is shown in table 2.

As shown in table 2, introduced oral cavity linked neurological disorders detection system such as intelligent guided particle local search algorithm based optimized neural network (IGPLONN) ensures minimum deviation value

TABLE 2. Error rate measured in different oral cavity linked neurological disorders prediction systems.

Methods	No. of patients									
	5	10	15	20	25	30	35	40	45	**50**
GABPNN	80.1	43.6	70.2	65.4	50.6	54.7	50.2	52.1	45.3	**31.2**
PSO-RBNN	83.2	55.5	72.1	66.6	44.5	43.4	66.3	65.2	66.5	**32.2**
BCCNN	87.3	56.5	74.1	88.7	66.2	62.4	76.5	74.3	73.5	**35.1**
(IGPLONN)	88.4	65.4	54.3	42.8	31.1	35.5	20.7	22.4	15.4	**11.4**

compared to other methods such as Genetic optimized back propagation neural network (GABPNN) [42], Particle swarm optimized radial basis function network (PSO-RBNN) [43] and Bee colony optimized convolution neural network (BCCNN) [44]. The effective utilization of features and its penalty process helps determine objective function, which selects the best features from the collection of a candidate solution. In addition to these selected features, auction and lp boosting process predict the oral cavity linked brain features effectively. The effective process reduces the deviation of the expected and predicted value; the graphical representation of the result is depicted in figure 9.
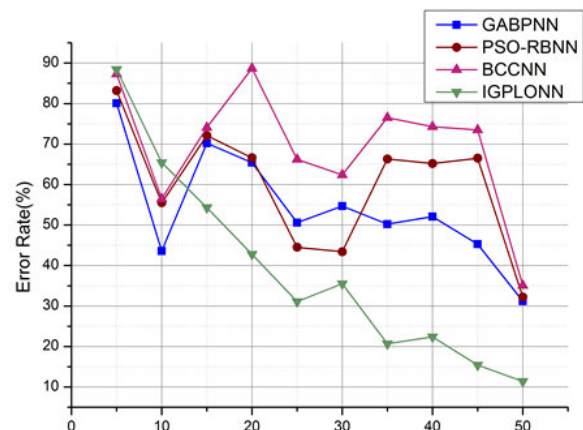

FIGURE 9. Error rate measured in different oral cavity linked neurological disorders prediction systems.

Figure 9 indicates that IGPLONN ensures minimum deviation value (11.4%) compared to other methods such as GABPNN (31.2%), PSO-RBNN (32.2%) and BCCNN (35.1%). The minimum deviation of IGPLONN helps identify the oral cavity linked neurological disorders with high accuracy.

B. SENSITIVITY AND SPECIFICITY

The selection of the oral cavity feature efficiency is determined using sensitivity and specificity value that is shown in table 3. The sensitivity value and specificity value is evaluated

TABLE 3. Sensitivity and specificity for different oral cavity linked neurological disorders prediction systems.

Methods	Sensitivity	Specificity
Genetic optimized back propagation neural network (GABPNN)	79.82	80.34
Particle swarm optimized radial basis function network (PSO-RBNN)	81.21	83.55
Bee colony optimized convolution neural network (BCCNN)	87.32	86.74
intelligent guided particle local search algorithm based optimized neural network (IGPLONN)	97.23	96.43

using Eqn (12 and 13) [54].

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (12)$$

$$Specificity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (13)$$

Table 3 demonstrates that the sensitivity and specificity value of the oral cavity linked neurological disorders prediction systems for 50 patients. IGPLONN attains high selectivity and prediction rate due to the minimization of the weak classifier as well as updating of weights values using an effective training algorithm. Along with this, the guided search algorithm selects only effective features that improve the overall oral cavity linked brain disease detection process. The effective training, objective, activation function improves the overall selection and prediction rate compared to other methods such as GABPNN, PSO-RBNN and BCCNN. The obtained results are depicted in figure 10.
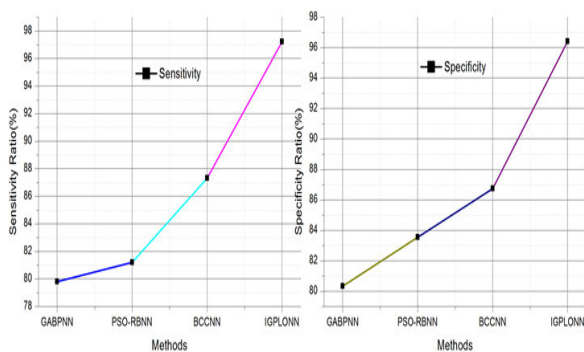

FIGURE 10. Sensitivity and specificity for different oral cavity linked neurological disorders prediction systems.

Figure 10 indicates IGPLONN obtained high selection and prediction rate (sensitivity-97.23%, specificity-96.43%) compared to other methods such as GABPNN (sensitivity-79.82%, specificity-80.34%), PSO-RBNN (sensitivity-81.21%, specificity-83.55%) and BCCNN (sensitivity-87.32%, specificity-86.74%). The effective selection of oral cavity linked central nerve disorders-related

TABLE 4. f-measure for different oral cavity linked neurological disorders prediction systems.

Methods	No. of patients									
	5	10	15	20	25	30	35	40	45	**50**
GABPNN	43.4	71.5	42.6	61.6	51.5	46.7	86.8	78.2	55.2	**91.3**
PSO-RBNN	55.3	72.8	54.9	63.2	42.4	83.3	66.3	82.3	66.1	**66.4**
BCCNN	66.5	85.7	56.2	84.2	62.5	82.9	77.2	72.7	72.1	**76.6**
(IGPLONN)	73.6	86.6	61.1	87.3	83.6	65.8	87.5	82.6	88.4	**96.3**

feature selection process improves the overall disease recognition rate.

C. F-MEASURE

The excellence is evaluated using an f-measure metric that is computed as follows [52]:

$$F\ measure = 2.\frac{precision.recall}{precision + recall} \quad (14)$$

Based on the derivation, the obtained f-measure value of intelligent guided particle local search algorithm based optimized neural network (IGPLONN) is depicted in table 4.

Table 4 demonstrates that f-measure value of oral cavity linked neurological system disorders detection systems; it is clear that IGPLONN obtains high prediction rate compared to other methods such as GABPNN, PSO-RBNN and BCCNN. As discussed earlier, the effective weight utilization, weight updating, activation process, an objective function improves the overall classification rate. The effective utilization of these parameters, recognize the oral cavity linked brain disease features are recognized effectively. The respective f-measure value is depicted in figure 1.

Figure 11 indicates that IGPLONN attains maximum accuracy (96.3%) compared to other methods such as GABPNN (91.3%), PSO-RBNN (66.4%) and BCCNN (76.6%).
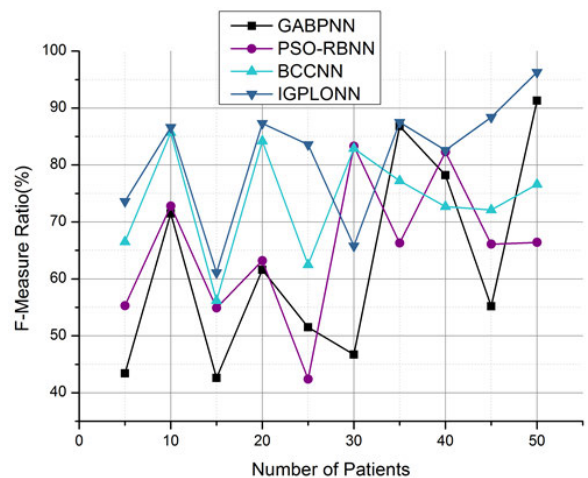

FIGURE 11. F-Measure for different oral cavity linked neurological disorders prediction systems.

TABLE 5. Matthews's correlation coefficient for different oral cavity linked neurological disorders prediction systems.

Methods	No. of patients									
	5	10	15	20	25	30	35	40	45	**50**
GABPNN	45.4	72.5	44.6	65.6	50.5	49.7	82.8	78.2	56.2	**90.3**
PSO-RBNN	55.3	73.8	57.9	66.2	44.4	88.3	67.3	90.3	65.1	**67.4**
BCCNN	65.5	87.7	59.2	89.2	66.5	90.9	76.2	74.7	73.1	**77.6**
(IGPLONN)	72.6	88.6	65.1	90.3	80.6	60.8	85.5	83.6	89.4	**98.3**

FIGURE 12. Matthews's correlation coefficient for oral cavity linked neurological disorders prediction systems.

FIGURE 13. Oral cavity feature analysis prediction ratio.

FIGURE 14. T-test measurement.

D. MATTHEWS CORRELATION COEFFICIENT

In addition to this discussed metrics, the excellence of the Oral cavity linked neurological disorders detection system efficiency is further evaluated using Matthews's correlation metric that is calculated using Eqn (15) [53].

Matthews correlation coefficient
$$= \frac{(TP * TN) - (FP * FN)}{(TP + FP)(TP+FN)(TN+FP)(TN + FN)} \quad (15)$$

From the eqn (15), the estimated value is shown in table 5.

According to table 5, having the Matthews coefficient value of oral linked with neurological disorders detection value. From the analysis IGPLONN successfully examines the interrelation between the oral cavity and brain disease perfectly compared to remaining methods such as GABPNN, PSO-RBNN and BCCNN. The introduced IGPLONN approach has an effective objective function, and each feature has a specific penalty value that effectively predicts the relationship between each feature. The successful analysis process improves the overall recognition rate [48], [49], and the obtained result is shown in figure12.

Figure 12 indicates that IGPLONN attains maximum accuracy (98.3%) compared to other methods such as GABPNN (90.3%), PSO-RBNN (67.4%) and BCCNN (77.6%). Thus IGPLONN approach identifies the oral cavity
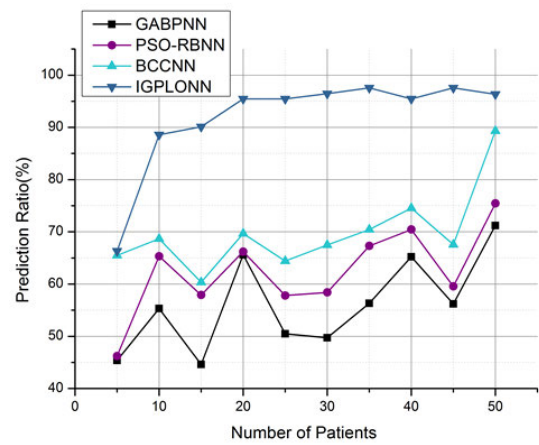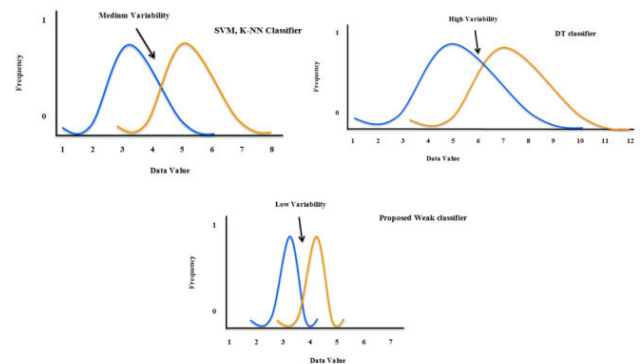
with brain problems perfectly, which helps minimize the future brain-related problem effectively.

As inferred from the Eq(2), where *x* is denoted as particular input from the list, $\lambda = \{\lambda k_1 \dots . k_p\}$ is the rate parameter of distribution ($\lambda > 0$). Based on the process, the importance of data is identified to minimize the representation of oral cavity data effectively. After that, various features derived from the list, which includes the entropy, average, correlation, maximum, minimum, probability, standard deviation information is derived [50], [51]. The extracted features maintained to get the knowledge about the oral cavity linked nervous problems are identified. The corresponding feature analysis is shown in figure 13; the graph shows that IGPLONN outperforms other methods in terms of prediction ratio.

In this paper, a statistics t-test has been performed with benchmark classifiers and compared the output of these classifiers to the proposed weak classifier. The proposed classifier achieves low variability compared to other classifiers. Figure 14 shows the t-test measurement of the proposed IGPLONN.

Among the several studies, the dental surgeon has a direct link with the nervous system because the problem in dental creates several neurological disorders. Hence, the oral cavity

and related issues are needed to be addressed in the beginning stage to improve the function of the central nervous system. The oral cavity prediction process does not have any reliable parameters to detect occult metastasis and proper tracheal intubation, which leads to creating complexity while maintaining the central nervous system.

V. CONCLUSION AND FUTURE WORK

This paper has proposed and evaluated the intelligent guided particle local search algorithm with optimized neural network (IGPLONN) for oral cavity linked neurological disorders prediction in IoMT platforms. In addition to the medical field, the Internet of Things (IoMT) has extent its legs in dentistry and offers the Internet of Dental Things (IoDT) model. There are multiple uses of IoMT in the dental field that have significantly revolutionized diagnostic and treatment mechanics. IoMT has transformed the outlook of the biomechanical and ideology treatment aspects of the medical sector. In our proposed system, initially, the oral cavity features are collected from the ICCR oral cavity datasets. The collected information related features are extracted for every patient, which is large in dimension. Hence, the over fitting (i.e., unwanted) data and dimensionality of features are minimized with the help of feature penalty, (i.e., objective function) and the cost function of the feature. Further, the features selection process is improved using particle position and velocity updating process. The selected features are processed using the back propagation neural network, and weak features are reduced with the help of the lp boosting method. Finally, classification is done using multiple layer convolution networks that recognize the oral cavity linked brain disease successfully. The excellence of the system is assessed utilizing MATLAB based outcomes in which the suggested IGPLONN method attains the maximum accuracy of 98.3% compared to other methods. For the future work, we plan to examine other optimization techniques that can be utilized to discover more relationships between neurological disorders and dental and brain images.

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