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Improving the Efficiency of Dental Implantation Process Using Guided Local Search Models and Continuous Time Neural Networks With Robotic Assistance

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ABSTRACT Nowadays, robotics plays a vital role in medical applications, especially in dentistry, where robots can track oral hygiene and perform dental surgeries. Dental implant replacement is one of the most challenging issues in dental surgery; quality procedures and safety measures need to be considered during this process. Manual dental implant is usually incapable to reach the satisfactory levels of accuracy and safety. In addition, it requires well-trained dentists and consumes a long time. Therefore, robot-assisted surgery systems are of utmost importance for dental implant placement as they can maintain higher level of dental examination precision and safety. More specifically, robotic arms can be manufactured with intelligent models for drilling identified locations in teeth. These intelligent robots have a high degree of autonomy, can automatically adjust during intraoperative procedures, and can execute dental surgical tasks directly on patients without any apparent control by a surgeon. In this article, we propose a novel approach to develop a robot-assisted intelligent system that improves the efficiency of dental implant process based on Guided Local Search with Continuous Time Neural Network (GLCTNN). Firstly, dental facts are collected from PubMed articles and Maryland school children datasets. Secondly, using the collected facts, an intelligent robot-assisted model based on GLCTNN is developed. The second step comprises data preprocessing to remove unsolicited details, extracting useful features from the clean data, and utilizing the extracted features to train the GLCTNN model. The proposed system recognizes the implantation location with high accuracy and maximizes implantation rate. The efficiency of the system is evaluated using experimental analysis at lab scale. The proposed GLCTNN-based approach ensures maximum average accuracy (99.5%) and minimum average deviation error (0.323) compared to W-J48, Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighboring (KNN), Nearest Neighbors with Structural Risk Minimization (NNSRM) and Generalized Regression Neural Network (GRNN) approaches.

INDEX TERMS Robotics, robot arm manufacturing, dental implantation, tooth root replacement, neural networks.

I. INTRODUCTION

According to several statistics of dental care, millions of people were affected by tooth decay, tooth loss, injuries and periodontal disease [1]. Traditional dental care provides only a reasonable treatment for missing teeth; however, dental

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implant is currently available as a promising solution for many dental problems. Dental implant is the process of tooth root replacement in which a strong foundation is provided to the teeth that helps match with the natural tooth [2]. During this process, an artificial tooth root similar to the natural tooth is placed on the jawbone. The jawbone is the base for the crown or artificial teeth; a connector or abutment is then placed on the dental implant top for supporting

the crown [3]. This process is performed by well-trained and experienced team of dental specialists such that the artificial tooth is felt similar to the natural teeth [4]. In 1951, American Academy of Implant Dentistry presented the implantology knowledge to share their experience of the dental implants and improve implant performance [5], [6]. Also, in 1952, Swedish Orthopedic introduced the titanium fuses to focus on dental implants in mouth. According to their discussions, dental implants have several advantages such as feeling like own teeth in appearance, enhancing speech, feeling comfort, eating easier, improving self-esteem, and enhancing oral health, durability, and convenience. Due to its enormous benefits, three millions of people were subject to dental implants, this number increases by around 500,000 annually [3]–[6]. Manual dental implants required a well-trained team to address the problem in teeth and experienced dentists to treat the patient in the right way [7]. The root implant is traditionally performed with titanium that is attached to the jaw in a very secure manner; this implant process takes almost 12 weeks to heal [3]–[7]. Although the dental implant process succeeded up to 98%, the exact location of implant place has to be detected by experts in a process that consumes a long time [8].

To overcome the problems associated with manual dental implants, robots are used to perform the dental implant process due to their high accuracy and low error rate. The high precise sensors are used and required in many applications [9], [10]. The robots required accurate sensors and controls to provide effective results. Robotic surgery is constantly developing, and its applications are growing continuously. The first robotic dental surgery system in the United States is approved for dental implant procedures in 2017 by the Food and Drug Administration. At the end of 2017, Zhao and colleagues created the world's first autonomous dental implant placement device in China [4]–[8]. Using this system, robots have performed a dental implant process to a woman; this was the first fully automated dental implant surgery in the world [3]–[8]. The robots have been manufactured and continuously trained, then, they have been monitored by dentists for their prediction accuracy of dental implant locations [11]; robot found implants with 0.2 to 0.3 mm of human error [12]. According to the report of science and technology daily dentistry in China, most of the dental treatments and surgeries, especially narrow oral cavity, were resolved accurately by robots [42]. Florida-Neocis FDA approved the first robotic system, 'Yomi', in 2017 for dental implant treatments and surgeries [13], [14]. This automated dental surgery robot reduced the human intervention in dental field and minimized errors. Moreover, the robot improved the efficiency of implant process in terms of precision and accuracy compared to manual implant process. Currently, robot-assisted remote surgery is one of the most effective autonomous surgical developed in touch health Leading Telehealth Company. Robots are continuously trained by critical dental data such as bone quality, medical status, biomechanical details, and surface characteristics to accomplish the implantation process

with affordable cost, maximum accuracy and minimum time. Although, robotics is being utilized in many dental applications, cutting-edge technologies are still needed to adapt with the surgery and image related treatments; additional information is required while performing dental restoration process. For this purpose, robotic arms are being developed for the teeth crowns and bridges during the implantation process [15]. Neural networks are used in different medical applications such as Detecting dental problem related brain disease [16] and tumor detection [17], [18]. Neural networks are integrated with robotics to improve its quality results.

The purpose of this work is to show how intelligent robots can be utilized to improve the efficiency of dental implantations. In particular, we propose a novel approach to develop a robot-assisted intelligent system that improves the efficiency of dental implant process based on Guided Local Search with Continuous Time Neural Network (GLCTNN). Firstly, dental data are collected from PubMed articles and Maryland school children dataset. Secondly, using the collected data, an intelligent robot-assisted model based on GLCTNN is developed. The second step comprises data preprocessing to remove unwanted details, extracting useful features from the cleaned data, and utilizing the extracted features to train the GLCTNN model. The proposed system identifies implantation locations with high accuracy and maximizes implantation rate with minimum time complexity. The efficiency of the system is evaluated using experimental analysis at lab scale. The proposed GLCTNN approach ensures maximum average accuracy (99.5%) with minimum average deviation error (0.323) compared to W-J48, Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighboring (KNN), and Nearest Neighbors with Structural Risk Minimization (NNSRM) and Generalized Regression Neural Network (GRNN) approaches.

The rest of this article is organized as follows: in section 2, we give an overview of robot-assisted dental implant process; section 3 reviews the various authors' opinion about dental implantation. Section 4 describes the proposed intelligent robot-assisted system for dental implantation, section 5 demonstrates the efficiency of the proposed system, and section 6 concludes the research.

II. ROBOT-ASSISTED DENTAL IMPLANTATION

As discussed earlier, dental implantation is the process of fixing Titanium mental pin in jawbone to perform the teeth restoration process [19]. During this process, several basic steps are needed. Firstly, a hole needs to be drilled in jawbone and maintain the grip to avoid loose fitting. Secondly, platform should be prepared for fixing the prosthetic teeth. Thirdly, abutment has to be used to fix the ceramic teeth on jawbone. These three steps of dental implantation process require 60 to 90 minutes with more concentration and precision. In addition, implantation process suffers from complexity while fixing artificial teeth on a bridge that also consumes most of the surgery time. To overcome these issues, robotic arms are being developed [15] in order to reduce the

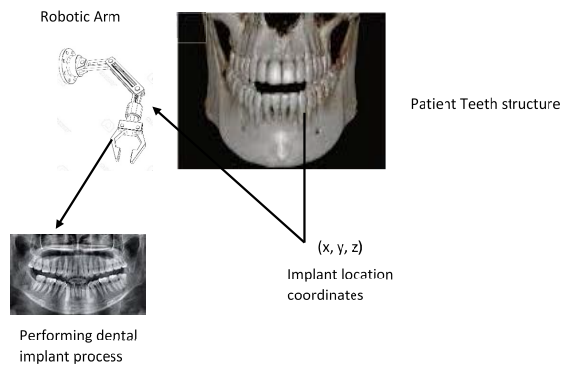


FIGURE 1. Robotic arm based dental implant process structure.

implantation complexity, time consumption, angulation error, landmark identification and improve the overall implantation efficiency. The main intension of robots in dental implant is to predict the exact location for insertion on jawbone which needs the maximum degree of anatomical precision. Robotic arms are developed with intelligent models for dental drill to attain short healing time and exact drilling location with excellent safety procedures. First, the dentist needs to examine the teeth and the relevant coordination by manual process. The collected coordinate details are fed into a software program that computes the cylindrical coordinates. The computed position is a three orthogonal vector linear combination; these vectors move an independent motor in particular direction to complete the drilling process. Miniature robotic basic model is used to develop the robot arm to complete the drilling process in teeth. The micro motors are placed in robotic arm to accomplish drilling effectively. The successful identification of locations and movements improve the implantation process in clinical analysis [20]. Once the exact point is identified, then the artificial teeth can be placed successfully with minimum time compared to the manual process. The sample model of the manufactured robotic arm for dental implant process is depicted in figure 1.

III. RELATED WORKS

This section analyzes different researches regarding the robotic based dental implant process for dental care and restoration process.

In [21], Sadat *et al.*, predicted successive rate of dental implant. The system collected the dental implant details from patient which were processed by several machine learning techniques. The system used the neural network, W-J48, support vector machine, naïve bayes and k-nearest neighboring approach. These methods successfully analyzed the implant information by optimizing the method parameters. These methods were combined to obtain the effective results while predicting successive measure. Then, the efficiency of the system was evaluated using experimental analysis, in which the system ensured 13.3% of sensitive indicator. Thus, the introduced system determined the implantation reliability and the implantation process.

In [22], Adriano Lorena Inácio Oliveira *et al.*, analyzed several machine learning techniques such as k-nearest neighboring, support vector machine, constructive radial basis network and Nearest Neighbors with Structural Risk Minimization (NNSRM) approaches. Initially, dental implants data was collected from patients for analyzing the successive rate of the implantation process. The collected data was processed by defined machine learning techniques which predicted the successive measure according to the patient history. From the analysis, the successive factors were considered for upcoming implantation process. Then, the excellence of the system was evaluated using the 10-fold cross validation approach in which introduced system ensured the maximum results on implant successive rate prediction process.

In [23], Khan, A. and Maity *et al.*, analyzed implantation cutting surface, roughness and material which were utilized in implantation process using generalized regression neural network. The network predicted the amount of titanium utilized while performing the implantation process. The efficiency of the system was evaluated using different cutting speed with 0.12 mm feed rate. The excellence of the system was examined in terms of using flank wear, cutting force and surface roughness. Thus, the introduced method successfully recognized the teeth restoration material with maximum accuracy. Then, the system recognized teeth restoration materials with 5% of error.

In [24], Tengfei Cui *et al.*, demonstrated experiments for analyzing the robot assisted based craniomaxillo facial surgery process. The effective robot assisted system was developed to predict the exact position to inject the needle while doing surgical operations. During this process, system used the master slave control and motion control process for detecting the accurate needle position that helped to improve the surgical accuracy. The excellence of this craniomaxillo facial surgery process was evaluated using different parameters such as kinematic simulation, identification, parameters and phantom experiments. From the analysis, system detected the needle position with highest accuracy and with maximum feasibility of robot system.

In [25], Mahmoud K. Al-Omiri *et al.*, analyzed the dental implant process, rehabilitation, splinting teeth criteria using the PubMed and MEDLINE articles. Initially, different articles for the implantation process were analyzed for predicting the number of clinical trials, long term materials, meta-analysis and randomized process. From the analyzed data, different decisions were taken to perform the dental implantation in terms of acceptability, minimum cost, and minimum complexity. Thus, the study provided the recommendation for the dental implantation and treatment process successfully.

In [26], Vadims Klimecs *et al.*, analyzed bone loss after performing 5 years of the dental implantation process. Initially, implantation details were collected from Riga Technical University and Biomaterial Development Care. The collected information consisted of bone loss details and filling information of 18 patients. These details were analyzed after

5 year of implantation process using the computed tomography to detect the problems in dental implant. Then, the developed system effectively utilized the restoration material with exact range, the implant surgery maintained their stability, also, having normal alveolar bone in teeth.

In [27], Yonggui Wang *et al.*, developed three arms surgical robot for assisting the mandible reconstruction surgery. During this process, different diseases information such as trauma, congenital disease and other diseases information could be collected. The gathered information was processed by robotic sub-process, optical measurements, image subsystem and patient system. These systems examined the details using robotic arm that predicted the hand eye coordination along with position was identified to perform the fibular implantation process. The successful recognition of skull model predicted the surgical position with maximum accuracy that led to improve the entire robot arm based surgical process.

Based on the above analysis of the previous work, we conclude that the quality of dental implant process can be improved by utilizing a robot-assisted intelligent system. Therefore, the main contributions of this article based on the analysis of various authors work are as follows:

- Creating an effective robot-assisted intelligent system for dental implantation process.
- Improving dental implantation process successive and accuracy rate using robotic-based system.
- Reducing the complexity and time while applying automatic robotic system.
- Improving the overall efficiency of robot learning process by applying the intelligent technique called guided local search with continuous time neural network (GLCTNN).

IV. THE PROPOSED APPROACH FOR IMPROVING DENTAL IMPLANTATION EFFICIENCY

This section proposes a novel approach to develop a robotic-based system for enhancing the dental implantation process efficiency. The proposed approach to develop this system consists of two stages: data collection and system construction; the second stage comprises three phases which are: 1) data preprocessing, 2) feature extraction and 3) GLCTNN model training.

A. DATA COLLECTION

For the purpose of this study, implantation data were gathered from the PubMed [6] using manual analysis process. The PubMed articles are stored using big data analytics model which consists of large volume of articles. The articles, bibliographies and other reviews were collected up to September 2014. The limitation of dental implant, laboratory details, clinical reports, short- or long-term studies, retrospective, cohort and prospective clinical analysis were included. These articles contained information about teeth implant process, supports, teeth joints, splinting implants, connection of rigid, teeth intrusion, non-rigid connection, standing implants, teeth connected implants, and combined

teeth implants. A total of 78 articles were selected to obtain details about dental implantation process. Dental implant details also include patient age, blood group, microbiota, jawbone details, material and tissue information. From these articles, we can conclude that the dental implantation process requires the automatic robotic system for improving the implantation accuracy and minimizing time consumption [28], [29]. In addition to PubMed articles, dental caries details are collected from Maryland school children dataset [30]; the dataset consists of several prevalence data which was examined from 1276 school children. The children were examined continuously to obtain the dental caries data such as name, age, gender, number of dentist visits, toothache caries and other dental care details.

B. CONSTRUCTION OF THE ROBOT-ASSISTED INTELLIGENT SYSTEM

The collected data are utilized to construct a robot-assisted intelligent system to improve the efficiency of the dental implant process. The construction process consists of three steps including data preprocessing, extracting relevant features and training the GLCTNN model. The flow diagram of system construction is depicted in figure 2.

1) DATA PREPROCESSING

The collected dental details have several missing and irrelevant data which needs preprocessing step to remove the unwanted items. Further, the normalization process changes dental data value into particular range that is 0 to 1. This normalization process minimizes the computation complexity while predicting the implantation location; the coefficient variance approach [31] was utilized for normalization. This method is also named the relative standard deviation which normalize the dental value according to the distribution probability value. During this process, system computes standard deviation σ and mean value μ for the data. The estimation is as follows:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^N (x_i - \mu)^2} \quad (1)$$

$$\mu = \frac{1}{n} \left(\sum_{i=1}^n x_i \right) \quad (2)$$

where, μ is denoted as the mean value, and σ is standard deviation of specific row. The coefficient variance value is computed as follows:

$$\text{coefficient value} = \frac{\sigma}{\mu} \quad (3)$$

The coefficient variance value is applied to the specific dental details row for normalizing the data. During this process, the distribution of specific data is computed for obtaining better normalized dental dataset. The Poisson distribution is used to compute the distribution of specific dental information in dental implantation process as follows [43]:

$$P(x \text{ present in interval } t) = e^{-rt} \frac{(rt)^x}{x!} \quad (4)$$

where, x is the particular data in the list, and r is the unit of time of one data appearance. Based on the data distribution,

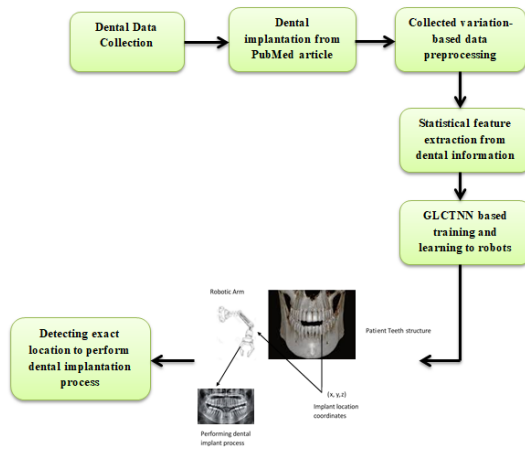


FIGURE 2. Structure of the proposed robotic-assisted dental implant system.

dental data is normalized effectively. This normalization process minimizes the missing value in dataset and reduces the computation complexity effectively.

2) FEATURE EXTRACTION

Various statistical features were obtained from the collected dental details in order to compute the exact locations of implants [32]. The extracted features are standard deviation, mean, dissimilarity, entropy and correlation.

Dissimilarity of the dental information need to be computed to obtain the affected part information, as follows [44]:

$$\text{Dissimilarity} = \sum_{i,j=0}^{n-1} |i - j| P(i, j) \tag{5}$$

where, n is the number of dental details; and i, j is dental information.

The entropy of feature should be computed to predict the importance of dental details while performing the dental implantation process. The entropy is computed as follows [45]:

$$\text{Entropy} = \sum_{i,j=0}^{n-1} -\ln(P_{ij})P_{ij} \tag{6}$$

Furthermore, the correlation between two dental data is computed using equation (7), correlation is used to estimate the dental caries and restoration information relationship details [46].

$$\text{correlation} = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i - \mu)(j - \mu)}{\sigma^2} \tag{7}$$

3) GLCTNN TRAINING

As shown in the figure 2, the robotics are continuously trained by the extracted dental implant features; the training process utilize the GLCTNN approach. This approach is one of the effective Artificial Neural Networks (ANT); it is used to predict the relationship among the dental features. The network generates the connectivity of one feature to another feature based on graph theory; therefore, the implant feature relationship is predicted using a directed graph. The directed graph is defined as a set of vertices connected by

edges with specific direction. Moreover, the continuous time network uses the internal memory that stores and processes the implant data successfully [33]. The network analyzes the implant details into finite impulse (similar information) and infinite impulse. During this process, finite impulse process is unrolled network that uses the directed acyclic graph while predicting the implantation process. The infinite impulse process does not have any rolling process that uses the directed cyclic graph. Therefore, the relationship between the dental material utilization and dental implantation process should be recognized effectively since it is used to train the robots for performing automatic implantation process. The entire output of the network is stored in the state that is used to improve the neural network training process. Therefore, the network uses the ordinary differential equation to train the robot according to the dental features. Considered incoming dental input with neuron as i, that is processed by network for obtaining the output of the network y_i . Then, the training process of particular input is computed as follows [34]:

$$\tau_i \dot{y}_i = -y_i + \sum_{j=1}^n \dot{w}_{ji} \sigma(y_j - \Theta_j) + I_i(t) \tag{8}$$

where, τ_i is represented as the postsynaptic node time constant value. Postsynaptic is the nervous process in which the information is passed from one node to another node. Θ_j is represented as the node bias value, $I_i(t)$ is denoted as the node input, y_i is the node activation function, \dot{y}_i is denoted as the change of activation value of node, and w_{ji} is the weight connection between the nodes. $\sigma(x)$ is represented as the given input (x) sigmoid function, which is computed as follows:

$$\sigma(x) = \frac{1}{(1 + e^{-x})} \tag{9}$$

Based on this process, the derived implantation inputs are fed into the robots for training to obtain the exact location of surgery. Further, the introduced continuous time-based neural network ability is applied in the evolutionary robots for addressing the successful training process [35]. The network weights and bias values should be continuously updated to minimize the deviation presented in the system. Further, network needs to be optimized using guided local search approach to improve the efficiency of the training process. The introduced approach is one of the effective meta heuristic method [36]; it presents the penalties for every optimized implantation feature search process. This approach predicts the objective function to obtain the local optimum value of a given input. For every patient, implantation problem is different and the implant location changes. Therefore, the solution is optimized according to the patient’s needs and the training is occurred according to the type of the problem. Each dental implantation feature f_i has the specific cost function that is represented as c_i , and the feature related with the specific penalty p_i . This initialization process helps to maintain the number of appearance of features in the local minima process. Based on the records, the feature indicators are used to compute the solution for the particular implant details. During this network updating process, the guided

TABLE 1. Error rate of intelligent robotic training

Methods	Number of Dental Implantation Patients									average score
	1000	2000	3000	4000	5000	6000	7000	8000	9000	
W-J48	0.46	0.408	0.447	0.405	0.43	0.461	0.43	0.435	0.431	0.434
NB	0.431	0.465	0.482	0.473	0.431	0.462	0.478	0.418	0.428	0.452
SVM	0.401	0.369	0.399	0.372	0.413	0.363	0.332	0.393	0.373	0.379
KNN	0.36	0.37	0.342	0.35	0.337	0.331	0.398	0.383	0.394	0.363
NNSRM	0.464	0.398	0.44	0.458	0.415	0.394	0.438	0.395	0.449	0.428
GRNN	0.3726	0.34	0.357	0.322	0.3742	0.33	0.379	0.33	0.347	0.35
GLCTNN	0.34	0.33	0.322	0.310	0.329	0.321	0.31	0.328	0.319	0.323

search process penalizes the features and the maximum utility value is computed as follows:

$$util(x, i) = I_i(x) \frac{c_i(x)}{1 + p_i} \quad (10)$$

where, x is input, i is number of times, $I_i(x)$ is denoted as particular input, $c_i(x)$ is represented as cost function and p_i is penalty.

According to this process, each dental implantation input is successfully examined, continuously monitored and provided to the robots for implantation process. Depending on the continuous training, robotic arms can predict the exact location of implantation process. If the location is difficult to obtain, the continuous time neural network approach is used. The deviation of the prediction is minimized using the guided local search approach. The efficiency of this intelligent learning process is further illustrated using experimental results and analysis.

V. RESULTS AND DISCUSSION

Extensive experiments have been conducted in order to demonstrate the efficiency of the proposed system in predicting the exact dental implant locations. Different performance metrics have been used to measure efficiency including error rate, precision, recall, F1-score and Matthews Correlation Coefficient (MCC). In the experiments, each patient implant details are identified; the identified values are used to train the GLCTTN model which precisely predicts the exact location of dental implant. Drilling is then performed by the robotic arm in the exact location for completing the implantation process. The training process is implemented using MATLAB tool and the respective PubMed dataset [37]. The successful training of robots helps minimize the error in predicting the implantation location in teeth [38].

A. ERROR RATE

Table 1 shows the deviation values (i.e., error rates) of GLCTNN as compared to several approaches including W-J48, Naïve Bayes (NB), Support Vector Machine (SVM), k-nearest neighboring (KNN) [21], Nearest Neighbors with Structural Risk Minimization (NNSRM) [22], and General-

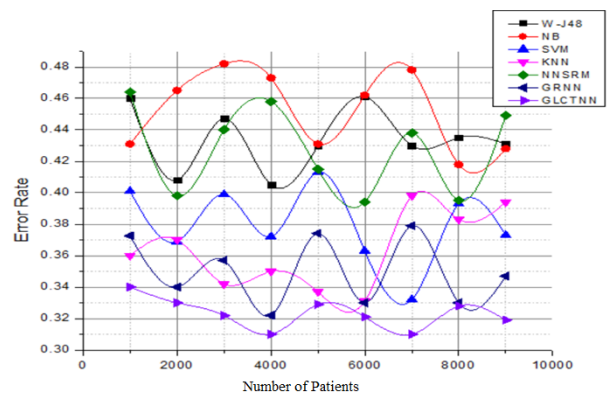


FIGURE 3. GLCTNN-error rate.

ized Regression Neural Network (GRNN) [23]. The results show that GLCTNN approach attains the minimum average error rate (0.323%) compared to all other approaches which are W-J48 (0.434%), NB (0.452%), SVM (0.379%), KNN (0.363%), NNSRM (0.428%) and GRNN (0.35%); these error rates are also shown in figure 3. The minimum error value leads to maximize accuracy of location identification process.

B. PRECISION AND RECALL

The efficiency of the system is also evaluated in terms of the precision and recall [47]. These metrics are computed based on equations 11 and 12.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (11)$$

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

The effective selection of implantation location details from the collection of training data is measured using precision metrics. From the collection of selected values, exact location is detected according to the patient characteristics which is evaluated using recall value. The obtained precision and recall values are presented in table 2.

The effective computation of implant features processing activation function predicts the exact implantation location.

TABLE 2. Precision and recall value of intelligent robotic training

Methods	Precision	Recall
W-J48	96.57	96.23
Naïve Bayes (NB)	96.98	96.47
Support Vector machine (SVM)	97.45	97.21
K-Nearest Neighboring (KNN)	97.89	97.53
Nearest Neighbors with Structural Risk Minimization (NNSRM)	98.46	98.13
Generalized Regression Neural Network (GRNN)	98.89	98.43
Guided Local search with Continuous Time Neural Network (GLCTNN)	99.43	99.03

Also, the Meta heuristic computation process reduces the error by utilizing penalty concept that improves the accurate implant location identification process. If the new incoming implant feature comes into the automatic robot implant detection system, the method utilizes the previous analysis for predicting the location with effective manner. The results in table 2 shows that GLCTNN attains higher precision and recall values compared to all other methods. GLCTNN achieved precision (99.43%) and recall (99.03%) due to the effective processing and activation function. This excellency of precision and recall values are compared to the traditional classifiers including W-J48 (precision-96.57%, recall-96.23%), NB (precision-96.98%, recall-96.47%), SVM (precision-97.45%, recall-97.21%), KNN (precision=97.89%, recall-97.53%), NNSRM (precision-98.46%, recall-98.13%) and GRNN (precision-98.89%, recall-98.43%); these values are also shown in figure 4. The increased precision and recall values directly indicate that the GLCTNN approach attains the maximum training accuracy of implantation process.

C. F1-SCORE

The efficiency of the system is also determined using F1 score [48] which is computed according to equation (13).

$$F1 - Score = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{13}$$

TABLE 3. F1-score of intelligent robotic training.

Methods	Number of Dental Implantation Patients									average score
	1000	2000	3000	4000	5000	6000	7000	8000	9000	
W-J48	95.78	95.82	96.03	96.23	95.98	96.02	95.24	96.32	95.87	95.92
NB	96.24	96.81	96.48	96.82	96.39	96.72	96.84	96.20	96.39	96.54
SVM	97.04	97.31	97.48	97.39	97.59	97.43	97.51	97.89	97.83	97.5
KNN	97.97	97.89	98.08	97.90	98.13	98.16	98.27	97.90	98.32	98.07
NNSRM	98.34	98.67	98.73	98.68	98.41	98.65	98.75	98.42	98.57	98.58
GRNN	98.478	98.85	98.8	98.73	98.65	98.97	98.90	98.74	98.68	98.76
GLCTNN	99.03	99.23	99.42	99.31	99.52	99.10	99.29	99.31	99.45	99.3

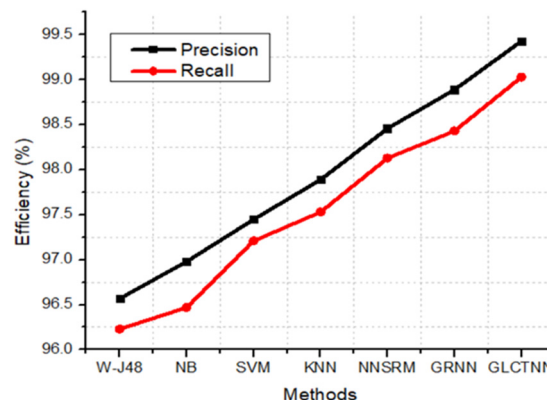


FIGURE 4. GLCTNN-precision and recall.

As shown in Table 3, the proposed GLCTNN approach attains maximum F1-score value compared to W-J48, NB, SVM, KNN, NNSRM and GRNN approaches; the obtained results are shown in figure 5. The GLCTNN approach ensures maximum average training accuracy (99.3%) compared to the W-J48 (95.92%), NB (96.54%), SVM (97.5%), KNN (98.07%), NNSRM (98.58%) and GRNN (98.76%).

D. MATTHEWS CORRELATION COEFFICIENT

The excellence of the system is further demonstrated using Mathew’s correlation coefficient value which is used to predict the relationship between the selected implantation location and trained details. The relevant Matthews coefficient value is estimated as follows [49]:

$$\begin{aligned}
 & \text{Matthews correlation coefficient} \\
 & = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{14}
 \end{aligned}$$

The results in table 4 shows GLCTNN approach has more relationship between one dental implant selected feature [50] and implant surgery performing location [51]. The obtained results present the highest values of Matthews Correlation Coefficient (MCC) for GLCTNN approach compared to other approaches including W-J48, NB, SVM, KNN,

TABLE 4. Matthews correlation coefficient (MCC) of intelligent robotic training.

Methods	Number of Dental Implantation Patients									average score
	1000	2000	3000	4000	5000	6000	7000	8000	9000	
W-J48	96.68	96.82	96.82	96.73	96.92	96.654	96.92	96.81	96.94	96.81
NB	97.267	97.377	97.36	97.65	97.23	97.457	97.25	97.46	97.31	97.37
SVM	97.57	97.7	97.83	97.98	97.53	97.85	97.69	97.83	97.68	97.74
KNN	98.32	98.35	98.67	98.21	98.52	98.42	98.49	98.54	98.32	98.43
NNSRM	98.58	98.79	98.98	98.37	98.78	98.68	98.82	98.86	98.79	98.74
GRNN	99.03	99.10	99.04	99.17	99.3	99.13	99.23	99.31	99.21	99.17
GLCTNN	99.34	99.57	99.265	99.76	99.48	99.52	99.49	99.62	99.49	99.5

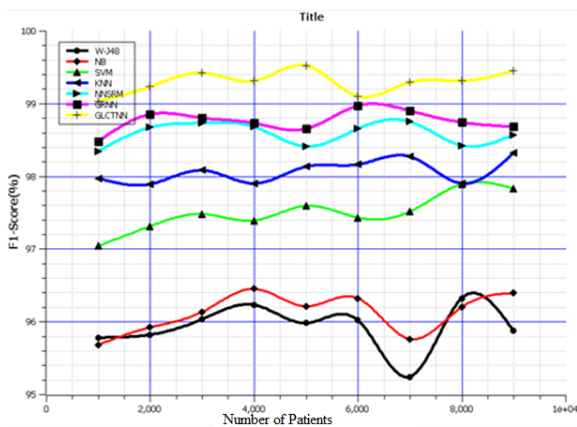


FIGURE 5. GLCTNN -F1-score.

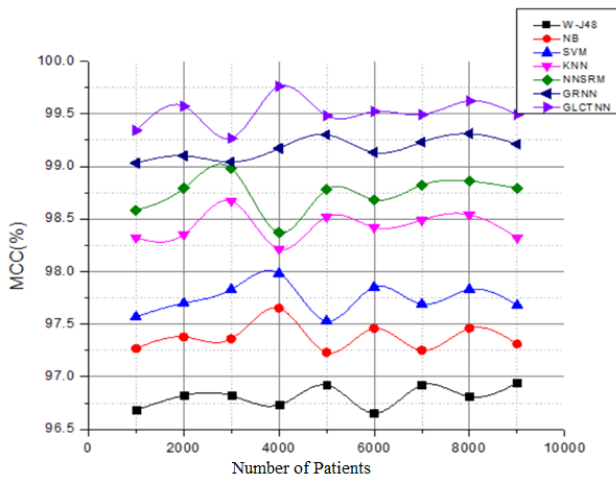


FIGURE 6. GLCTNN-MCC.

NNSRM and GRNN. The relevant graphical analysis is also shown in figure 6. Figure 6 shows that GLCTNN approach ensures maximum average training accuracy (99.5%) compared to the W-J48 (96.81%), NB (97.37%), SVM (97.74%), KNN (98.43%), NNSRM (98.74%) and GRNN (99.17%). As discussed earlier, the well trained and learned automatic robotic-based dental implantation process ensures the proposed listed contribution and maintains the highest accuracy.

Based on the above results, the proposed system precisely predicts the implant location from the training data. Also, the system obtained the implantation location [52] with minimum time complexity compared to other method. The proposed GLCTNN method uses the postsynaptic node time constant value that monitor the time consumption for this location predicting process. From the various analyses, the system time complexity [47] is measured according to the number of time multiplication process performed (n_{mul}) and activation function (n_g) used while predicting the dental implantation location [53]. Therefore, the time complexity is computed as follows:

$$\text{Time Complexity} = n_{mul} + n_g \tag{15}$$

and the time complexity of GLCTNN network is computed as follows:

$$\text{time} = \sum_{k=2}^{n \text{ layers}} \left(n^{(k)} n^{(k-1)} n^{(k-2)} \right) + \left(n^{(1)} n^{(0)} 1 \right) + \sum_{k=1}^{n \text{ layers}} \left(n^{(k)} \right) \tag{16}$$

$$n_{mul} = n \text{ layer} \cdot n^3 \tag{17}$$

$$n_{mul} = n \cdot n^3 = O(n^4) \tag{18}$$

$$n_g = n \text{ layer} \cdot n = O(n^2) \tag{19}$$

The time complexity is computed as $O(n^\alpha)$ in which complexity is varied according to the number of layers used in the network. The effective training and learning process [54] helps minimize the time complexity and enhanced the efficiency of dental implantation process. Thus, we can conclude that the proposed GLCTNN robot-assisted dental implantation system successfully performs the clinical surgery using the training data.

VI. CONCLUSION AND FUTURE WORK

This article proposed a robotic-assisted system for dental implantation. An intelligent model is developed with the robotic arm to perform the implantation process. The developed robots are trained by applying the continuous time neural network; the training process is further optimized by applying the Meta heuristic guided search algorithm which uses the features and relevant penalty for predicting

the exact location of implantation process. This process effectively identifies the accurate location with maximum average accuracy (99.5%) and minimum average deviation error (0.323) compared to W-J48, Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighboring (KNN), Nearest Neighbors with Structural Risk Minimization (NNSRM) and Generalized Regression Neural Network (GRNN) approaches. This work can be extended by applying the optimized neural network to predict the interior details for implantation process.

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