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ARTIFICIAL NEURAL NETWORKS TO DETECT FACIAL ABNORMALITIES THROUGH CEPHALOMETRIC RADIOGRAPHY USING BJORK ANALYSIS

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Abstract

The dental and skeletal relationships in the head are studied in Cephalometric analysis. This research work addresses Bjork's analysis for the classification of patients. In this research work, the backpropagation neural network (BPNN), and generalized regression neural network (GRNN) classifiers are used and studied for the diagnosis of Cephalometric analysis. In this study, a total of 304 (male 109, female 195) patient's case records were collected for this study. All the collected clinical data are used for classification. For training and testing the proposed models, patients' data were separated by four-fold cross-validation. Based on Bjork analysis, experimental results show that GRNN provided achieving the performance of 97.39% of good classification results when compared to the BPNN model. The GRNN approach is feasible and was found to be achieving a performance of 97.39% of the correct detection of patients.

Keywords:

Bjork's Analysis, Cephalometric Analysis, Back Propagation Neural Network, Generalized Regression Neural Network

1. INTRODUCTION

Cephalometrics shows skeletal structures of the head to assess growth and development. Certain irregularities of the position of the jaw can also show up in this analysis. One can provide a computerized analysis that will measure and compare the anatomy to assist in the treatment plan.

Cephalometrics has established itself as one of the pillars of comprehensive orthodontic diagnosis. It is also a valuable tool in treatment planning and follows up on patients undergoing orthodontic treatment.

- Cephalometrics helps in orthodontic diagnosis by enabling the study of skeletal, dental, and soft tissue structures of the craniofacial region.
- It helps in the classification of the skeletal and dental abnormalities and also helps in establishing facial type.
- Cephalometrics helps in planning treatment for an individual.
- Cephalometrics helps in predicting the growth-related changes and changes associated with surgical treatment.

Cephalometric analysis is the study of the dental and skeletal relationships in the head. It is frequently used by dentists, often orthodontists in particular, as a treatment planning tool [1].

Artificial neural networks (ANN) are the result of academic investigations that use mathematical formulations to model nervous system operations. The resulting techniques are being successfully applied in a variety of everyday applications. Classification is an essential decision-making tool, especially for the diagnosis of diseases. Unfortunately, while many classification procedures exist, many of the methods suffer in the presence of statistical outliers or overlapping groups. An ANNs have been suggested as tools for classification [2].

Neural networks (NN) represent a meaningfully different approach to using computers in the workplace. A NN is used to learn patterns and relationships in data. The data may be the results of market research effort, a production process has given varying operational conditions, or to diagnose the diseases in medicine as well as dental. Regardless of the specifics involved, applying a NN is substantially different from traditional approaches. These advancements are due to the creation of NN learning rules, which are the algorithms used to 'learn' the relationships in the data. The learning rules enable the network to 'gain knowledge' from available data and apply that knowledge to assist a doctor in making key decisions [3].

Cephalometric analysis requires an expert system to be developed for computer applications in this field. So preliminary research is necessary using backpropagation neural network (BPNN), and generalized regression neural network (GRNN) classifiers for making the computers to the detection of abnormalities in skeletal and dental. The dental and skeletal relationships in the head are studied in Cephalometric analysis. The Cephalometric analysis depends on Cephalometric radiography to study relationships between bony and soft tissue landmarks and can be used to diagnose facial growth abnormalities before treatment, in the middle of treatment to evaluate progress or after treatment to ascertain that the goals of treatment have been met. There is a lack of skilled personnel proficient enough in Cephalometric analysis and also to assist the doctor. There is a growing need for the computer as an aid for Cephalometric analysis. Calibrating cephalogram is a necessary step in making the computers to the detection of abnormalities in skeletal and dental.

The remainder of this paper is formed as follows: the assessment of the proposed work is presented in the form of a literature review in section 2. The techniques or methods applied to detect the abnormalities in skeletal and dental abnormalities are discussed in section 3. The various results of this work are presented in section 4. At last section 5 discusses the conclusion and suggestion for further research.

2. LITERATURE REVIEW

In this section, a review of literature about the various studies on the diagnosis of diseases, Cephalometric analysis, and automated Cephalometric analysis including ANNs are discussed.

2.1 STUDIES ON DIAGNOSIS OF DISEASES

NNs are being applied to an increasingly large number of real-world problems. Their primary advantage is that they can solve problems that are too complex for conventional technologies; problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be defined. In an algorithmic approach, the computer follows a set of instructions to solve a problem. Unless the specific steps that the computer needs to follow are known, the computer cannot solve the problem. That restricts the problem-solving capability of conventional computers to problems that we already understand and know how to solve. In general, NNs are well suited to problems that people are good at solving, but for which computers generally are not. These problems include pattern recognition and forecasting, which requires the recognition of trends in data. In the case of the NN, even for imprecise inputs, the network can retrieve the desired output or the data that is closest to the desired output. Considering the successful applicability of NNs in many areas, an endeavor to assess their performance for data retrieval forms the basis for this research work [4].

The major task of medical science is to prevent and diagnose diseases. Brause (2001) highlighted that almost all the physicians are confronted during their formation by the task of learning to diagnose [5]. Here, they have to solve the problem of deducing certain diseases or formulating a treatment based on more or less specified observations and knowledge [6]. Below some certain difficulties of medical diagnosis that have to be taken into account are listed.

The basis for a valid diagnosis, a sufficient number of experienced cases, is reached only in the middle of a physician's career and is therefore not yet present at the end of the academic formation. This is especially true for rare or new diseases were also experienced physicians are in the same situation as newcomers. Principally, humans do not resemble statistic computers but pattern recognition systems. Humans can recognize patterns or objects very easily but fail when probabilities have to be assigned to observations [7]. The quality of diagnosis depends on physician talent as well as their experiences. Emotional problems and fatigue degrade the doctor's performance. The training procedure of doctors, in particular specialists, is a lengthily and expensive one. So even in developed countries may feel the lack of MDs. Medical science is one of the most rapidly growing and changing fields of science. New results disqualify the older treats, new cures and new drugs are introduced day by day. Even unknown diseases turn up now and then. So, a physician should try hard to keep up to date [5]-[7].

Regarding the problems above and also many others, the question would be how computers can help in medical diagnosis. Since decades ago, computers have been employed widely in the medical sector. From local and global patient and medicine databases to emergency networks, or as digital archives, computers have served well in the medical sector.

Meanwhile, in the case of medical diagnosis, regarding the complexity of the task, it has not been realistic yet to expect a fully automatic, computer-based, medical diagnosis system. However, recent advances in the field of intelligent systems are going to materialize a wider usage of computers, armed with AI techniques, in that application. A computer system never gets tired or bored, can be updated easily in a matter of seconds, and is rather cheap and can be easily distributed. Again, a good percentage of visitors to a clinic are not sick or at least their problem is not serious, if an intelligent diagnosis system can refine that percentage, it will set the doctors free to focus on nuclear and more serious cases [8].

2.2 STUDIES ON CEPHALOMETRIC ANALYSIS

Cephalometric analysis is a useful diagnostic tool to determine the facial type and its growth pattern so that the clinician can determine facial disharmonies to centralize therapeutic measures during treatment and modify facial growth [9].

Cephalometric radiography provides information enabling the classification of skeletal and dental abnormalities. A Cephalometric radiograph is particularly useful for analysis of changes in the relationship of teeth to be basal bones, and, the anteroposterior position of maxilla, mandible, and teeth with each other [10].

The Cephalometric measurements required for treatment planning are not necessarily the same as those used to evaluate the results of treatment. It is important to establish the measurements that are necessary to provide the information required for treatment planning [11].

The numerous Cephalometric measurements that can be made are really necessary for therapeutic decision making, and whether the accuracy of diagnosis and the success of the treatment are improved by taking more measurements [11].

A comparative study of Steiner's and McNamara's Cephalometric analyses to determine the position of bone bases was performed in 51 patients and revealed the substantial similarity of the two techniques. The authors consider McNamara technique to be of greater and more immediate clinical value [12].

Jarabak [13] has defined Cephalometrics as the science that segments the dentofacial complex to assess the relationship among segments and how individual growth increments or their changes can affect the whole complex. Jarabak's Cephalometric analysis was based on the investigative studies of Bjork [14], which were applied to clinical conditions, making it possible to compare variations of shape, size, age, gender, and race.

Several skeletal malocclusions are defined during growth. The orthodontist who is interested in treating young patients will have to assess every specific growth pattern, thus knowing its directions and possibilities. Only after this, orthodontic mechanics will be chosen for better results and with less difficulty [9]. Jarabak [9] Cephalometric analysis can also predict the results of different orthodontic approaches. The analysis of lines and angles that define this analysis provides the clinician with the skeletal characteristics and, as a result, identification of muscular patterns. These can be directly applied to the selection of orthodontic or orthopaedic devices, in such a way that the clinician can be able to evaluate the facial growth response from these therapeutic procedures.

2.3 STUDIES ON AUTOMATED CEPHALOMETRIC ANALYSIS PRICES USING PNN

Cephalometry was first introduced by Broadbent and subsequently revolutionized the analysis of malocclusion and the underlying skeletal structures. Lateral Cephalogram may be traced manually, but most recently computers is used [15].

A microcomputer-based system that integrates image processing and computer graphics techniques to automate the data extraction and storage process in Cephalometric analyses. The system increases the consistency of measurements and improves the productivity of surgical and dental staff [16].

Two approaches may be used to perform a Cephalometric analysis: a manual approach, and a computer-aided approach. The manual approach is the oldest and most widely used. It consists of placing a sheet of acetate over the Cephalometric radiograph, tracing salient features, identifying landmarks, and measuring distances and angles between landmark locations [17].

In an automated Cephalometric analysis, a scanned or digital Cephalometric radiograph is stored in the computer and loaded by the software. The software then automatically locates the landmarks and performs the measurements for Cephalometric analysis [17]. The challenging problem in an automated Cephalometric analysis is landmark detection, given that the calculations have already been automated with success [17].

Different ANN paradigms were employed to provide a vertical diagnosis through both supervised and unsupervised learning. The training set utilized for NN learning was constructed based on data obtained from 210 patients [18].

The purpose of this study is to formulate the Cephalometric norms of the Saudi population and to evaluate whether significant Cephalometric differences exist between Saudi and Caucasian patients. Lateral Cephalometric radiographs of 60 selected Saudis (30 males and 30 females) with esthetically pleasing and harmonious faces, Angle I molar relationship, with all permanent teeth present and no history of orthodontic treatment or facial trauma, age range between 20 and 30 years were analyzed using the Downs and Steiner analysis. The means, standard deviations, and ranges of the measurements were compared with the norms established by Downs and Steiner. Statistically, several significant differences were noticeable in the results of the present study when the Cephalometric mean values for the selected Saudi population were compared with the norms suggested for a white Caucasian population by Downs and Steiner. The results of the present study are significant and showed normal Saudis have slightly protrusive maxillae, a tendency to Class II facial pattern, and a high mandibular plane (MP) angle. These results have clinical implications in the diagnosis and treatment of adult Saudis with dentofacial deformities [19].

Orthodontic diagnosis, however, often results in very difficult and influenced by subjective interpretation of the measured parameters. For this reason, ANN-based approaches have been proposed as a valid support for diagnosis in orthodontics [20].

During routine anesthesia, an airway physical examination should be conducted in all patients to estimate whether tracheal intubation is easy or difficult. In the clinic, some anesthetists usually do this by examining single items although most of the specialists agree that full consideration of multiple features of airway physical examination rather than single one would enable anesthetists to improve the prediction accuracy when encountering a difficult airway. The application of machine learning tools has shown its advantage in the medical aided decision. The purpose of this study is to construct a medical decision support system based on support vector machines (SVM) with 13 physical features for tracheal intubation prediction ahead of anesthesia. A total of 264 medical records collected from patients suffering from a variety of diseases ensure the generalization performance of the decision system. Moreover, the robustness of the proposed system is examined using a four-fold cross-validation method and results show the SVM-based decision support system can achieve average classification accuracy at 90.53%, manifesting its great application prospect of supporting clinic aided diagnosis with full consideration of multiple features of airway physical examination [21].

In modern orthodontic practice, great reliance is placed on systematic and objective methods of characterizing craniofacial forms, using measurements based on both hard and soft tissue landmarks. Lateral skull X-ray images are routinely used in Cephalometric analysis to provide quantitative measurements useful to clinical orthodontists. It is argued that a model- and knowledge-based methodology provides the best approach in successfully interpreting digitized lateral skull radiographs. A rule-based segmentation system, making use of an image appearance model, is used to extract image features from gray-level images. Complex image features and Cephalometric landmarks are constructed from these segmented component features. A predictive model, defining picture structure, allows location hypotheses to be made for image features. The underlying structure of the location model provides the basis for a geometric constraint model of use in discriminating between image feature candidates. A blackboard system is used to organize these tasks hierarchically, with individual knowledge sources grouped according to function and the individual stages of the adopted image interpretation cycle. Quantitative results demonstrate the superiority of this complex system over its component segmentation system run on its own. Comparisons with clinicians demonstrate both the strengths and weaknesses of the present system [22].

The projection of the software was based on the correct interpretation of the analysis to reach the goals of the treatment plan. The Orthodontic folder collects easy-to-complete and consults schemes of essential data, aided by sophisticated graphics that the modern informatics systems can supply. The orthodontist can, therefore, make use of, simply and rapidly, of the consultation to compare the results achieved. The method is that which is commonly called “Orthodontic check-up” [23].

Paraconsistent ANN is a mathematical structure based on paraconsistent logic, which allows dealing with uncertainties and contradictions. It proposes an application of paraconsistent ANN to analyze Cephalometric measurements to support orthodontics diagnostics. Orthodontic and Cephalometrical analysis taking into account several uncertainties and contradictions, an ideal scenario to be treated by a paraconsistent approach [24].

3. METHODOLOGY

Human beings can acquire and manipulate symbolic, pattern-based heuristic, and fuzzy knowledge in an ingenious manner. Researchers tried to develop an intelligent system with this capability by using a traditional artificial intelligent system and its techniques. Limited success in these ventures has led researchers to pursue other methods such as NNs, and fuzzy logic. Here the BPNN, and GRNN are considered to train and test the patient’s data for classification of abnormalities in skeletal and dental.

3.1 CEPHALOMETRICS

The assessment of craniofacial structures forms a part of the orthodontic diagnosis. The earliest method used to assess facial proportions was by artistic standards with harmony, symmetry, and beauty as key points. Craniometry can be said to be the forerunner of Cephalometry. Craniometry involved measurements of craniofacial dimensions of skulls of dead persons. This method was not practical in living individuals due to the soft tissue envelop which made direct measurements difficult and far less reliable [25].

3.2 CEPHALOMETRIC LANDMARKS

Cephalometric makes use of certain landmarks or points on the skull which are used for quantitative analysis and measurements. The Cephalometric landmarks (Fig.1) can be of two types. The first one is anatomic and the second one is derived landmarks. The anatomic landmarks represent actual anatomic structures of the skull. The derived landmarks that have been obtained secondarily from anatomic structures in a Cephalogram. The landmarks that are used in Cephalometrics should fulfill certain requirements which are given below.

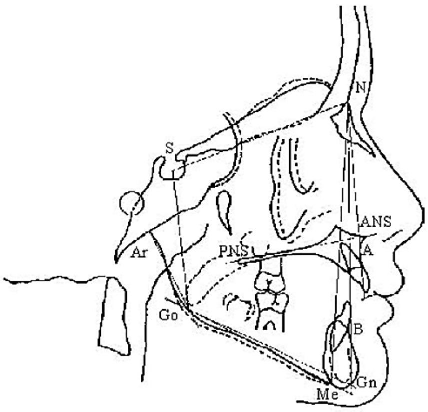


Fig.1. Cephalometric landmarks

- It should be easily seen in a radiograph.
- It should be uniform in outline and should be reproducible.
- Landmarks should permit valid quantitative measurements of lines and angles projected from them [26].

3.2.1 Landmarks:

Nosion (N): the most anterior point midway between the frontal and nasal bones on the frontonasal suture [26]. Sella (S): the point representing the midpoint of the pituitary fossa or sella turcica. It is a constructed point in the mid-sagittal plane. Point A (A): it is the deepest point in the midline between the anterior nasal spine and alveolar crest between the two central incisors. It is also called subspinale. Point B (B): it is the deepest point in the midline between the alveolar crest of the mandible and the mental process. It is also called supramentale. Gonion (Go): it is a constructed point at the junction of the Ramal plane and the MP. Pogonion (Gn): it is the most anterior point of the bony chin in the median plane.

3.3 CEPHALOMETRIC ANALYSIS

Cephalometric analysis is the study of the dental and skeletal relationships in the head. It is frequently used by dentists, often orthodontists in particular, as a treatment planning tool. There are various techniques can be applied to analyze the Cephalometric radiography. Four of the most popular methods of analysis used in orthodontology are the (i) Steiner analysis, (ii) Bjork's analysis, (iii) Ricketts analysis, and (iv) McNamara's analysis. In this research work, Bjork's analysis is discussed.

3.3.1 Bjork's Analysis:

In Bjork's analysis, the facial growth studies of the mandible demonstrated that certain stable structures in the mandible could consistently be relied upon as indicators of future growth rotation of this jaw. He also emphasized that these structural signs were only indicators and had the greatest predictive value in the more pronounced cases of mandibular growth rotations. Jarabak's Cephalometric analysis was based on the investigative studies of Bjork's analysis. In Bjork's analysis, the different parameters from various Cephalometric analyses are used to diagnose facial growth abnormalities prior to treatment.

- **Saddle Angle**: The N-S-Ar angle is the angle between the anterior and posterior cranial base. Within the region of the posterior cranial base lies a sagittal growth center, the sphenooccipital synchondrosis. The position of the fossa is determined by growth changes in this area. A large saddle angle indicates a posterior position, a small saddle angle an anterior position of the fossa. If this deviation in position of the fossa is not compensated by the length of the ascending ramus, the facial profile becomes either retrognathic or prognathic. The mean value is 1230±50 [2].
- **Articular Angle**: The S-Ar-Gn angle is one of those rare angles that may be altered by orthodontics. If the bite is opened by extrusion of the posterior teeth or by distalisation, the angle increases, whilst the mesial movement of the teeth will make it smaller. A larger articular angle imposes retrognathic changes on the profile, small angle on the other hand prognathic changes. It has been found that a reduced articular angle in all cases of prognathism. The mean value is 1430±60.
- **Gonial Angle**: the Ar-Go-Gn angle is an expression for the form of the mandible, with reference to the relation between body and ramus. The gonial angle also plays a role in growth prognosis. A large angle indicates more of a tendency to the posterior rotation of the mandible, with condylar growth directed posteriorly. A small gonial angle on the other hand indicates vertical growth of the condyles, giving a tendency to the anterior rotation with the growth of the mandible. The mean value is 1300±70.
- **Sum of the Posterior Angles**: the sum of the three above-mentioned angles (saddle, articular, and gonial angle) is 3960±60 (Brojk). This sum is significant for the interpretation of the analysis. If it is greater than 3960, the direction of growth is likely to be vertical; if it is smaller than 3960, growth may be expected to be horizontal.
- **L-MP Angle**: the posterior angle between the long axis of the incisor and the MP is determined. It has a mean value of 900±30. A wide-angle denotes protrusion of mandibular incisors, a smaller than normal angle, very upright incisors.
- **U-SN Angle**: The long axis of the upper incisor is extended to intersect the SN line and the posterior angle is measured. It has a mean value of 1020±20. Larger angles usually indicate maxillary incisor protrusion, smaller angles very upright incisors.

3.4 METHOD OF PATIENT DATA COLLECTION

In this study patient's data are collected from Raja Muthiah Dental College and Hospital (RMDC&H), Faculty of Dentistry, Annamalai University, Annamalai Nagar, Cuddalore District, Tamilnadu, India. A total of 304 (male 109, female 195) patient's case records were collected for this study. These 304 patients are having some facial abnormalities before treatment in skeletal, dental, and both parts.

3.5 MODELLING TECHNIQUES FOR CEPHALOMETRIC ANALYSIS

In this section, the BPNN, and GRNN modeling techniques are considered.

3.5.1 Backpropagation Neural Networks (BPNN):

NNs are an information processing technique based on the way biological nervous systems, such as the brain, process information. The fundamental concept of NNs is the structure of the information processing system. Composed of a large number of highly interconnected processing elements or neurons, a NN system uses the human-like technique of learning by example to resolve problems. The NN is configured for a specific application, such as data classification or pattern recognition, through a learning process called training [4].

The commonest type of ANN consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. There are three layers in ANN namely, input, hidden, output layer [4]. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

Backpropagation Algorithm has emerged as the standard algorithm for training of networks under the supervised form of learning. The algorithm derives its name from the fact that the partial derivatives of the performance measure with respect to the free parameters (synaptic weights and biases) of the network are determined by back-propagating the error signals through the network. In order to train a NN to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the NN compute the error derivative of the weights. In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The backpropagation algorithm is the most widely used method for determining the error derivative. In this research work, the BPNN is implemented using MATLAB NN toolbox.

3.5.2 Generalized Regression Neural Networks (GRNN):

The GRNN [27]-[29] is a feed-forward NN based on non-linear regression theory consisting of four layers: the input layer, the pattern layer, the summation layer, and the output layer.

While the neurons in the first three layers are fully connected, each output neurons are connected only to some processing units in the summation layer. The individual pattern units compute their activation using a radial basis function (RBF), which is typically the Gaussian kernel function. The RBF has a maximum of 1 when its input is 0. As the distance between the input vector and the weight vector decreases, the output increases. Thus, the radial basis neuron acts as a detector which produced 1 whenever the input is identical to its weight vector. One of the parameters for GRNN is the spread of RBFs. The spread default value is 1.0. In this research work, GRNN is implemented using MATLAB NN toolbox.

The larger spread is, the smoother the function approximation will be. To fit data closely, one can use a spread smaller than the typical distance between input vectors. To fit the data more smoothly a larger spread can be used. The summation layer has two different types of processing: the summation units and a single division unit. The number of summation units is always the same as the number of GRNN output units. The division units only sum the weighted activation of the pattern units without using any activation function.

The training of the GRNN is quite different from the training used for the BPNN. It is completed after the presentation of each input-output vector pair from the training set to the GRNN input layer only once; that is, both the centers of the RBFs of the pattern units and the weights in connections of the pattern units and the processing units in the summation layer are assigned simultaneously. The training of the pattern units is unsupervised but employs a special clustering algorithm, which makes it unnecessary to define the number of pattern units in advance. Instead, it is the radius of the clusters that need to be specified before the training starts. The GRNN computes the predicted values "on the fly" from the training values, using the basis functions defined below [30].

$$f(x_k) = \sum_{j=1}^{N} t_j \varphi_{kj} \,/ \sum_{j=1}^{N} \varphi_{kj},\, k = 1,2,...,M, \tag{1}$$

where φ_{kj} is the basis functions are Gaussian functions of distance in attribute space, which can be written as,

$$\varphi_{kj} = \varphi(d_{ij}) = \exp(-\frac{d_{ij}^2}{\sigma^2}), \qquad d_{ij} = \left|x_i - x_j\right|, \tag{2}$$

where is a smoothness parameter. In the RBF network, the computation of the predicted values is similar.

$$f(x_k) = \sum_{j=1}^{N} w_j \varphi_{kj},\, k = 1,2,...,M, \tag{3}$$

However, the weights are computed from the training data using the following linear equation.

$$t(x_i) = \sum_{j=1}^{N} w_j \varphi_{ij},\, i = 1,2,...,N, and\ \varphi_{ij} = \varphi(d_{ij}), \tag{4}$$

3.6 OBJECTIVES OF THE PROPOSED WORK

The following are the objectives of the proposed work.

- To identify the input and output parameters pertaining to skeletal and dental abnormalities for the various Cephalometric analysis.
- To extract the relevant parameter values.
- To normalize the various parameter values.
- To prepare patients with data for training and testing the BPNN, and GRNN classifiers by four-fold cross-validation.

- To classify abnormalities of the different patients with severity in skeletal and dental.

The above objectives can be fulfilled by the following corresponding sections.

3.6.1 Identification of the Input and Output Parameters:

With the consultation of the dentist, the following input and output parameters based on Bjork's analysis is identified from the case records of patients for abnormalities in skeletal and dental. To extract the various parameters, Bjork's analysis is very much useful. Seven input parameters were identified with abnormalities in skeletal and dental and six types of Cephalometric inference are identified as output parameters for abnormalities in skeletal and dental as given in Table.1 and Table.2 respectively.

Table.1. Bjork's analysis identified input parameters for abnormalities in skeletal and dental

Input parameters	**Mean value (degrees)**
Age	-
Sex	-
Saddle Angle (N-S-Ar)	123 ± 5^0
Articular Angle (S-Ar-Go)	143 ± 6^0
Gonial Angle (Ar-Go-Gn)	130 ± 7^0
Lower Incisor to MP	90 ± 3^0
Upper Incisor to SN	102 ± 2^0

Table.2. Cephalometric inferences are identified as output parameters for abnormalities in skeletal and dental (Bjork's analysis)

Output parameters	**Output value**
Horizontal Growing Face	0 or 1*
Vertical Growing Face	0 or 1
Lower Incisor Retrognathic	0 or 1
Upper Incisor Retrognathic	0 or 1
Lower Incisor Prognathic	0 or 1
Upper Incisor Prognathic	0 or 1

* 1 represents abnormalities and 0 represents normal

3.6.2 Extraction of Parameters:

These parameters are extracted from the patient's case records using lateral Cephalometric landmarks that are already discussed in section 3.2 and section 3.3.

3.6.3 Classification of Patients:

To classify abnormalities of the different patients with severity in skeletal and dental, the details are given in Table.2. The skeletal and dental have seven input parameters as given in Table.1. If a patient has abnormal values of all these parameters then the patient is in abnormalities in skeletal and dental. If a patient has got normal values of these parameters then the patient is normal. For example, 1, 0, 1, 0, 0, 1 represents the patient with horizontal growing face, lower incisor is retrognathic and upper incisor is prognathic in skeletal and dental.

3.6.4 Normalization of Parameter Values:

The development of the training network starts with the selection of several different combinations of input variables to evaluate the most reliable NN model.

For the pre-processing phase, all input and output data are normalized to values between 0 and 1. It is assumed that x has only finite real values and that the elements of each row are not all equal. The method is described by the following equation for converting any x_i value with normalized y_i value.

$$y_i = \frac{(y_{max} - y_{min})*(x_i - x_{min})}{(x_{max} - x_{min}) + y_{\min}} \tag{5}$$

This equation converts any x_i value into corresponding y_i value in the range of y_{min} to y_{max}. In this research work, the normalized value must be between 0 and 1 for Bjork's analysis. Therefore y_{min}=0 and y_{max}=1. Then y_{min}(0) and y_{max}(1) are substituted in above equation which yields,

$$y_i = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \tag{6}$$

3.6.5 Four-Fold Cross Validation of Data:

In this study, the four-fold cross-validation is applied for training and testing the BPNN, and GRNN. In four-fold cross-validation, the training set is randomly divided into 4 disjoint sets namely fold 1 (say p_1), fold 2 (say p_2), fold 3 (say p_3), and fold 4 (say p_4). Where each fold contains patients' case records. Further, these folds are formed with the folding groups for training and test data preparation for Bjork's analysis.

- **Group 1**: training: p_1+p_2+p_3 (76 + 76 + 76 = 228); testing: p_4 (76).
- **Group 2**: training: p_1+ p_2 + p_4 (76 + 76 + 76 = 228); testing: p_3 (76).
- **Group 3**: training: p_1+ p_3 + p_4 (76 + 76 + 76 = 228); testing: p_2 (76).
- **Group 4**: training: p_1+ p_3 + p_4 (76 + 76 + 76 = 228); testing: p_1 (76).

3.6.6 Confidence Score (CS):

To measure the performance of the BPNN, and GRNN a confidence score is computed by the equation.

$$CS = exp\left(-mse\left(actualValue - networkValue\right)\right)*100 \tag{7}$$

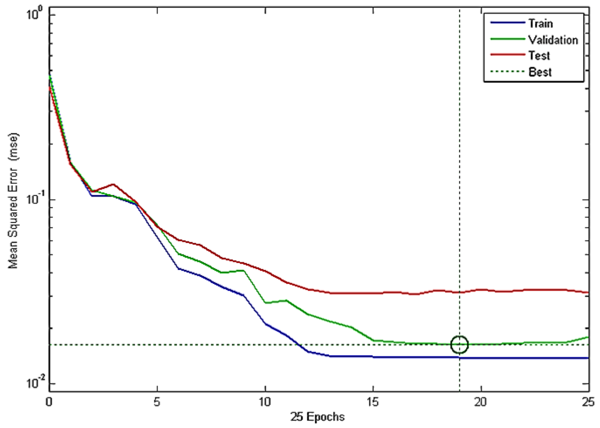
4. RESULTS AND DISCUSSION

In this chapter results about skeletal and dental patient's abnormalities data are presented and discussed in the form tables and graphs. During the training phase, the NN models are capable of reproducing the target output values with minimal error. Further, the reliability of the trained model in producing correct responses for a new set of data is examined. Once the training, testing, and validation phases are accomplished, the NN obtained can be used as a practical design tool.

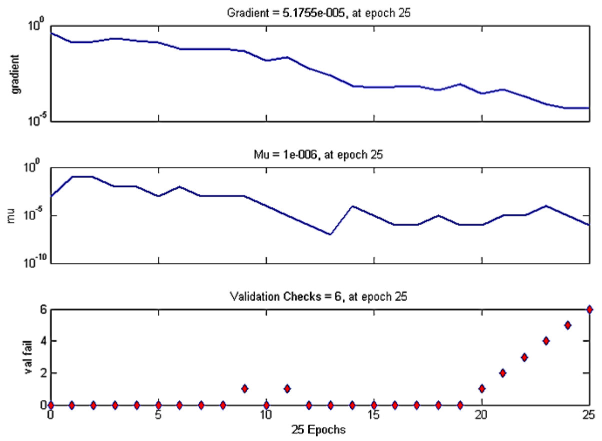
In this study, the four-fold cross-validation is applied for training and testing. The training and testing set is randomly divided into 4 disjoint sets of equal sizes. Let each set of data labeled as p_1, p_2, p_3, and p_4. The group 1 is represents cross-validation $p_1p_2p_3$ (training) vs. p_4 (test), group 2 represents cross-validation $p_1p_2p_4$ vs. p_3, group 3 represents cross-validation $p_1p_3p_4$ vs. p_2 and finally group 4 represents cross-validation $p_2p_3p_4$ vs. p_1.

4.1 BJORK'S ANALYSIS WITH BPNN MODEL

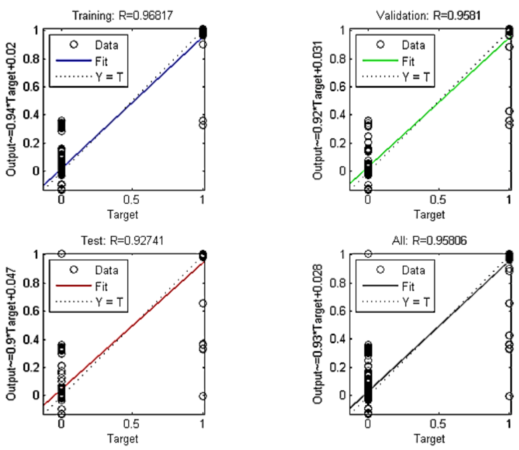
The Fig.2 to Fig.5 show the performance, training state and regression plot for group 1, group 2, group 3 and group 4 with abnormalities in skeletal and dental (Bjork's analysis) is tested in BPNN model.



(a)

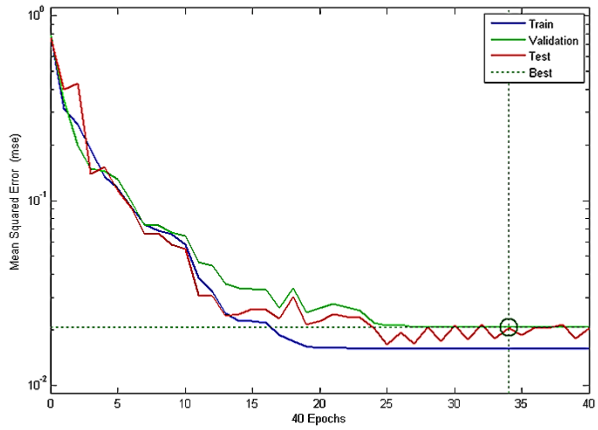


(b)

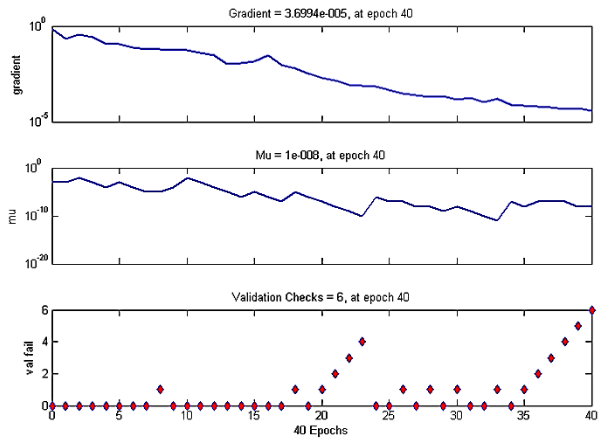


(c)

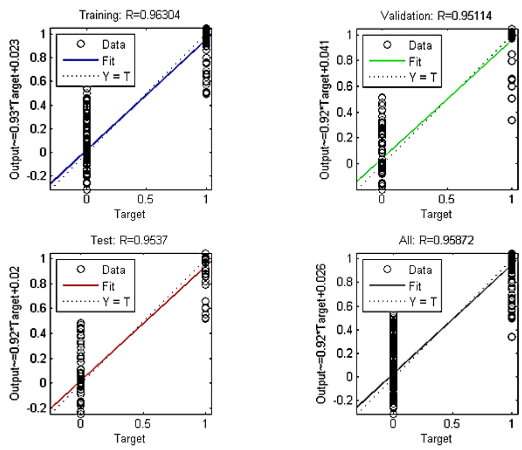
Fig.2. Group 1 Bjork's analysis (a) performance, (b) training state, and (c) regression plot



(a)



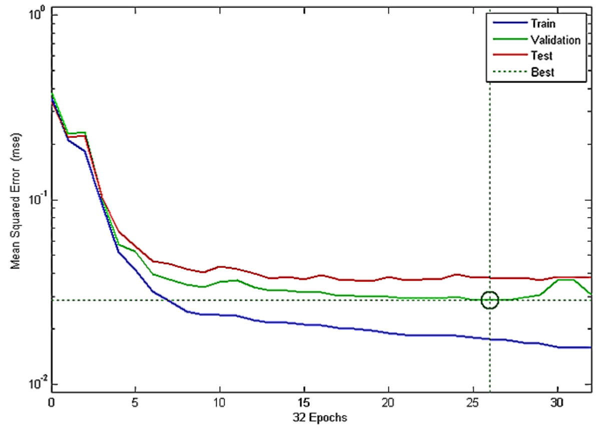
(b)



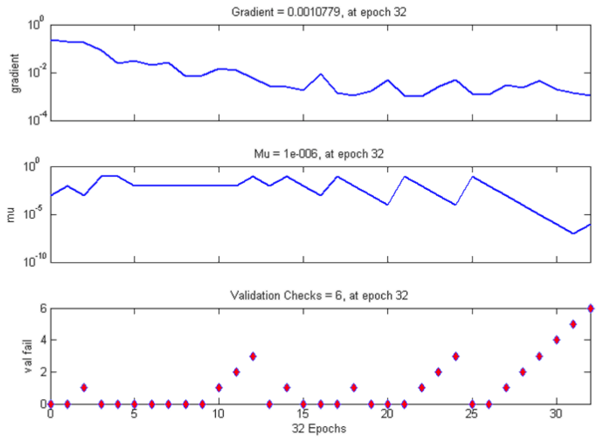
(c)

Fig.3. Group 2 Bjork's analysis (a) performance, (b) training state, and (c) regression plot

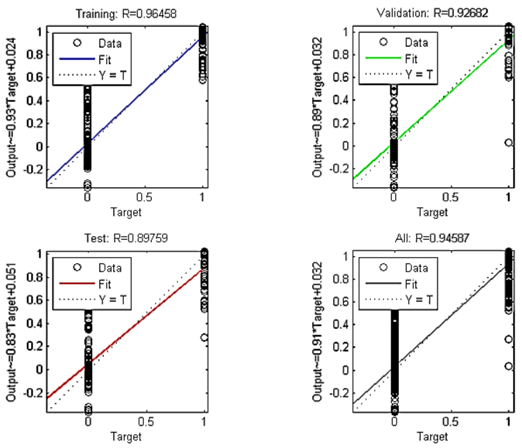
From Fig.2(a), Fig.3(a), Fig.4(a), and Fig.5(a) for the performance of BPNN can be seen by the reduction of mean square error (mse) values gradually epochs after epochs. From this one can conclude that the BPNN model learns for the training data to map the input and output parameters.



(a)

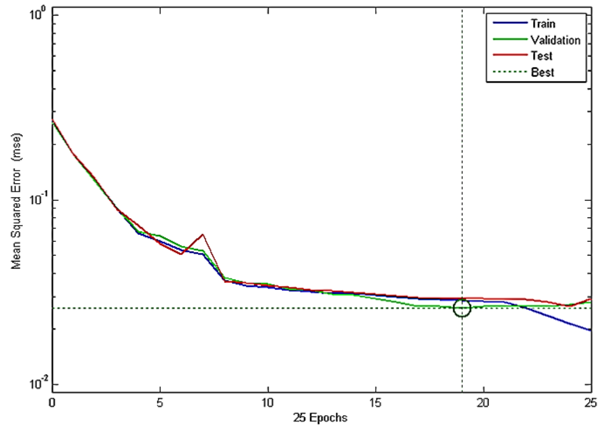


(b)

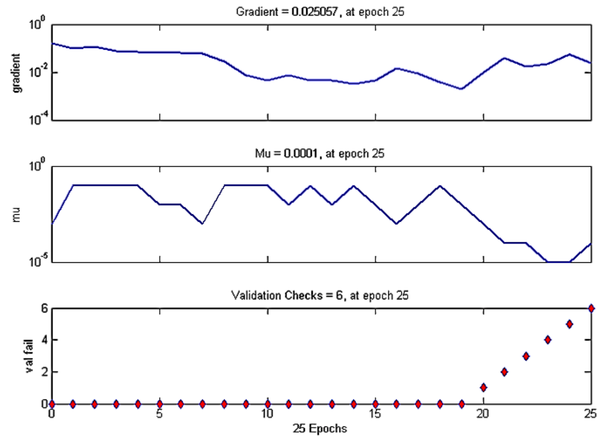


(c)

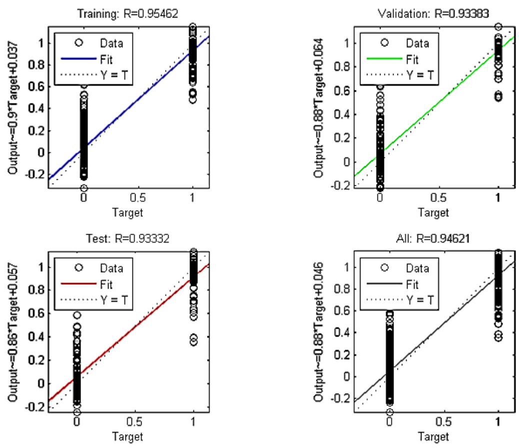
Fig.4. Group 3 Bjork's analysis (a) performance, (b) training state, and (c) regression plot



(a)



(b)



(c)

Fig.5. Group 4 Bjork's analysis (a) performance, (b) training state, and (c) regression plot

From Fig.3(b), Fig.3(b), Fig.4(b), and Fig.5(b) for training state one can observe that very low gradient and mu values and validation checks are performed for stepping the BPNN training.

From Fig.2(c), Fig.3(c), Fig.4(c), and Fig.5(c) for regression plot one can conclude that the BPNN achieves good performance for training, validation, test overall data with help of R values (approximately 0.92).

The Table.3 gives the incorrect responses for a new set of data for group 1, group 2, group 3, and group 4 with abnormalities in skeletal and dental (Bjork's analysis) is tested in the BPNN model. Form this Table.3 one can conclude that BPNN can give an average of 97.25% confidence score. The BPNN can map the input and output parameters by 97.25%.

Table.3. Performance in detection of abnormalities in skeletal and dental (Bjork's analysis) using BPNN

BPNN model	Test data (no.)	Number of abnormalities misclassified	Performance percentage		
			R Value	Actual	CS
Group 1	76	12	0.92	84.21	97.78
Group 2	76	8	0.95	89.47	97.72
Group 3	76	8	0.89	89.47	97.02
Group 4	76	10	0.93	86.84	96.46

4.2 BJORK'S ANALYSIS WITH GRNN MODEL

The Fig.6 to Fig.9 show the spread of RBF versus the performance predicted by GRNN in group 1, group 2, group 3, and group 4 respectively for test data.

From the graph at Fig.6 one can observe that the performance of GRNN increases for the spread values from 0 to 0.07. Maximum performance 96.91% occurs at the spread of 0.07. After that the performance of GRNN is gradually reducing for group 1.

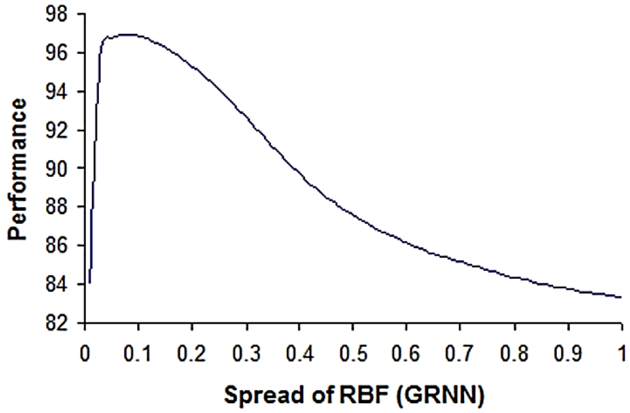


Fig.6. Group 1 Bjork's analysis for performance curve of skeletal and dental abnormalities

From the graph in Fig.9 one can observe that the performance of GRNN increases for the spread values from 0 to 0.1. Maximum performance 97.62% occurs at the spread of 0.1. After that, the performance of GRNN is gradually reducing for group 4.

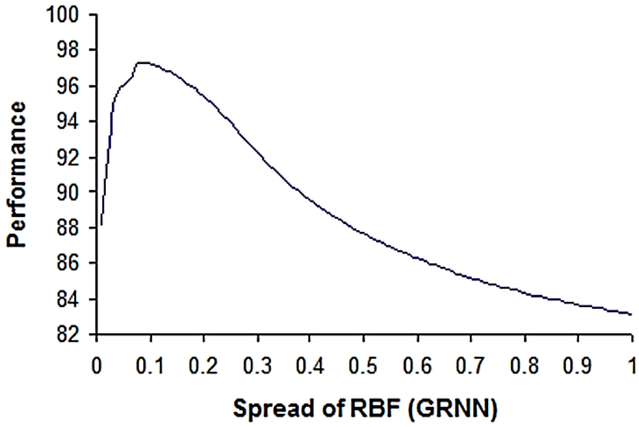


Fig.7. Group 2 Bjork's analysis for performance curve of skeletal and dental abnormalities

From the graph in Fig.7 one can observe that the performance of GRNN increases for the spread values from 0 to 0.08. Maximum performance 97.31% occurs at the spread of 0.08. After that, the performance of GRNN is gradually reducing for group 2.

From the graph in Fig.8 one can observe that the performance of GRNN increases for the spread values from 0 to 0.05. Maximum performance 97.71% occurs at the spread of 0.05. After that, the performance of GRNN is gradually reducing for group 3.

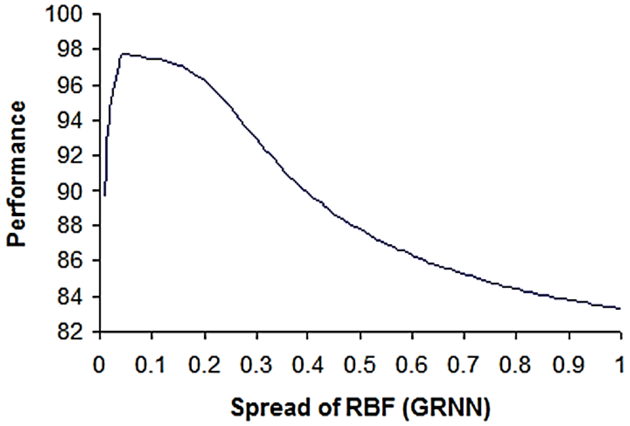


Fig.8. Group 3 Bjork's analysis for performance curve of skeletal and dental abnormalities

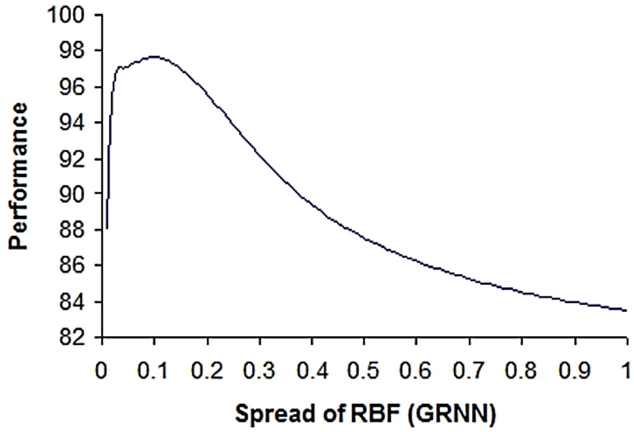


Fig.9. Group 4 Bjork's analysis for performance curve of skeletal and dental abnormalities

Table.4. Performance in detection of abnormalities in skeletal and dental (Bjork's analysis) using GRNN

GRNN model	Test data	Number of Abnormalities Misclassified	Performance in %	
			Actual	CS
Group 1	76	13	82.89	96.91
Group 2	76	11	85.52	97.31
Group 3	76	10	89.47	97.71
Group 4	76	14	81.57	97.62

The Table.4 gives the incorrect responses for a new set of data for group 1, group 2, group 3, and group 4 with abnormalities in skeletal and dental (Bjork's analysis) is tested in the GRNN model. Form Table.4, GRNN can classify the patients by 97.39% on the average.

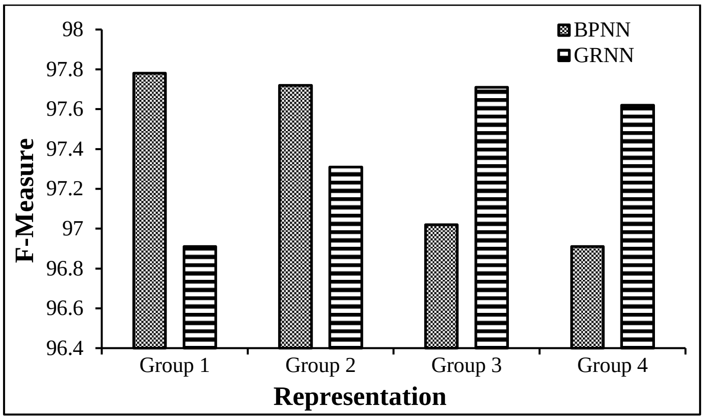


Fig.10. Performance for the various cross validation of skeletal and dental abnormalities (Bjork's analysis)

4.3 COMPARISON OF CLASSIFICATION RESULTS

The Fig.10 performs the various cross-validations of skeletal and dental abnormalities for Bjork's analysis. From this graph in Fig.12 one can observe that maximum performance is 97.78% occurred in group 1 BPNN model for the abnormalities in skeletal and dental when compared with GRNN model for Bjork's analysis. The experimental results show that GRNN provided achieving the performance of 97.39% of good classification results when compared to BPNN model.

5. CONCLUSION

In this research work classification of abnormalities in skeletal and dental by BPNN, and GRNN model is presented. For this classification input parameter of Cephalometric landmarks (input) and types of abnormalities (output) are identified, 304 (male 109, female 195) data collected, normalized, trained, tested, and classified using BPNN, and GRNN models. These parameters are used as input to the BPNN, and GRNN models. The types of abnormalities, namely prognathic (lower incisor and upper incisor), retrognathic (lower incisor and upper incisor), and vertical or horizontal growing face are also identified. According to the simulation results, the GRNN approach is feasible and was found to be achieving a performance of 97.39% of the correct detection of patients. From this one can conclude that the GRNN model is capable of reproducing the target output values with minimal error. In this study BPNN, and GRNN models are used to detect the abnormalities in skeletal and dental.

Further, this study can be modeled by other techniques like SVM, ELM, and Neuro-Fuzzy to see the improvement in the performance. Fuzzy logic can also be tried with these lines. Further, this study, to collect more patient case records and normalize, train, test, and classify by using BPNN, and GRNN models for other analyses like Steiner, Ricketts, and McNamara.

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