PERIODONTAL DISEASE RISK ASSESSMENT USING ARTIFICIAL NEURAL NETWORKS

PROPOSED RESEARCH WORK

1. Name of Scholar:
   (In English): RAJESH SHANKARAPILLAI

   (In Hindi):

2. Title of the Research:
   (In English)

"PERIODONTAL DISEASE RISK ASSESSMENT USING ARTIFICIAL NEURAL NETWORKS"

   (In Hindi)

3. Location:

4. IMPORTANCE/RATIONALE OF PROPOSED INVESTIGATION

Artificial neural networks are modeled after the neural networks in the brain. The neural net is a network of tiny processors that gives a computer the ability to sort through input, and arrive at conclusions by analyzing patterns in the data. Neural networks can, for example, learn to play a game, and improve their skills each time they play the game through cognitive modeling. There are also many business applications for a neural networks' artificial intelligence, particularly in business intelligence sectors, despite the limitations on neural network technology, and learning requirements. Artificial neural networks can be most adequately characterized as 'computational models' with particular properties such as the ability to adapt or learn, to generalize, or to cluster or organize data, and which operation is based on parallel processing. Neural networks are parallel, distributed, adaptive information-processing systems that develop their functionality in response to exposure to information. The unique learning methods employed by these provide a robust and non linear approach to approximating the target function for classification, regression, and clustering problems. Dental data mining is a relatively new research field where classic regression techniques are used for centuries without much concern over risk prediction or risk analysis techniques. Regression and decision tree algorithms routinely used in medical and dental statistics have comparatively less efficient predictive value when multi factorial etiology is proposed.

Natural Neural Networks

A natural neural network is composed of neurons, each connected to thousands of other neurons with synapses and dendrites. When a threshold of input is reached, an electrical signal is passed across by a firing synapse. The more times a particular path is followed, the stronger the path becomes. An artificial neural network mimics this organizational structure by connecting small processors together in the same fashion. Each artificial neuron has threshold similar to a biological neuron, and produces output based on the sum of the input.

Cognitive Processing in Artificial Neural Networks

The neurons in artificial neural networks are interconnected so that each result depends on the output level reached by other neurons. In this way, neural networks act essentially like a very complex, self-activating flowchart. If a certain neuron does not reach the threshold, the answer to that path is, "No", and another path is followed. If the neuron does reach its threshold, the answer is, "Yes", and the path continues to the next decision point. In this fashion, the neural network is able to reach a conclusion based on the information given as input. With more information, the network is better able to reach accurate conclusions.

Neural Networks are a form of artificial intelligence that use multiple artificial neurons, networked together to process information. This type of network has the capability to learn from patterns, and extrapolate results from data that has been previously entered into the network's knowledge base. This ability makes neural network applications extremely valuable to the medical industry, particularly in the area of in-office, or online medical diagnosis. Using neural nets as a data mining solution may allow medical facilities of the future to present patients with the option of receiving online medical advice from an artificial intelligence software program. A neural network's artificial intelligence, with cognitive modeling and structured learning algorithms, bring neural nets closer to independent reasoning than earlier AI.

5. SCOPE OF THE PROPOSED STUDY

Cognitive Modeling Improves Targeted Intelligence and Learned Behaviour

Neural networks can learn independently, but it is much more efficient to provide the network with learning algorithms. These algorithms essentially teach the neural network how to learn. It is necessary, also, to provide information to the neural network, and classify the information so that the network can process it correctly. Neural networks are becoming very useful in the medical field, due to their ability to reach independent conclusions based on data provided combined with 'learned' patterns. The medical applications of neural networks include the use of diagnostic programs, which apply all known symptoms to the knowledge base, and arrive at a diagnosis based on previous patterns. In business, neural networks can vastly improve the output resulting from Text Analytics in Data Mining Software. Internet Searches also benefit from Neural Networking technology.

Data mining, the practice of extracting patterns from past or current activity, can be paired with neural networks to provide essential medical business solutions. Business intelligence uses data mining to understand patterns, project future activity, and profit from it. Neural networks are perfectly suited for this use, due to their ability to use information to project an outcome. Potential current uses include marketing projections, financial projections, and even playing the stock market. We are planning to include it's application into the dental field by introducing it in the dental disease prognosis paradigm; where a vast majority of decisions purely depend solely upon the learned experience and previous treatment regimens.

Current Health Diagnosis Procedures

Clinicians use a combination of a patient's case history and current symptoms to reach a health diagnosis when a patient is ill. In order to recognize the combination of symptoms and history that points to a particular disease, the doctor's brain accesses memory of previous patients, as well as information that has been learned from books or other doctors. A neural network has the ability to mimic this type of decision-making process, and use a knowledge base of information, and a training set of practice cases, to learn to diagnose diseases. The implications of studies involving the use of neural network applications to provide diagnostic and predictive medical opinions are highly promising for the future of online medical advice, taking into consideration the fact that neural network applications continue to learn during use.

The neural network used to diagnose malignant melanoma, at the end of the initial training period, was able to correctly diagnose episodes of cancer as well as a trained medical professional. With each patient, however, the neural network application will become more accurate, and may eventually offer a more accurate diagnosis than a human physician (Gniadecka Philipsen et al. 2004) . A neural network's artificial intelligence, with cognitive modeling and structured learning algorithms, bring neural nets closer to independent reasoning than earlier AI.

Neural Network Applications at Home

As Neural Networks become more prevalent in the medical profession, they may begin to become popular tools for doctors and other medical facilities, in order to accomplish triage functions remotely. Combined with Smart Home

Appliances, this type of neural network has the ability to not only detect health problems, but diagnose them and initiate a call to emergency services or the family doctor as needed. Used in combination with a Smart Home Security System, an online medical diagnosis provided by artificial intelligence applications can save lives.

6. REVIEW OF WORK ALREADY DONE ON THE SUBJECT

"Artificial Neural Networks Can Accurately Predict Risk For Dental Diseases"

The ***key concepts of neural network*** based systems are explained and the potential applications of such systems in dentistry are evaluated in the Journal of Dentistry article by Brickley, Shepherd & Armstrong (Brickley Shepherd et al. 1998) titled "Neural Networks: A New Technique For Development Of Decision Support Systems In Dentistry". They concluded that neural networks may initially seem complex and computer intensive, but in truth actually integrate well with a clinical environment. Neural network expert systems may be trained with only clinical data and as such can be used where 'rule based' decision making is not possible and this is the case in many clinical situations. Artificial Neural networks may therefore become important decision making tools within dentistry and have applications both in improving clinical care and in maximizing the cost benefit of dental care.

Risk is the probability that an event will occur (Burt 2001). In epidemiology, it is most often used to express the probability that a particular outcome will occur following a particular exposure. In Last's *Dictionary of Epidemiology*, (Last 2001) a risk factor (a term only in use since the 1960s) is defined as: an aspect of personal behavior or lifestyle, an environmental exposure, or an inborn or inherited characteristic which on the basis of epidemiological evidence is known to be associated with health-related condition(s) considered important to prevent. There are very few conditions that constitute a sufficient cause in chronic and infectious disease (a sufficient cause being one where a specific exposure will always result in a particular outcome). If there were, it would not be necessary to deal with risk, which often deals with varying degrees of necessary cause (a necessary cause being an exposure that must always precede a particular outcome), though it can also deal with exposures that are neither necessary nor sufficient causes.2

There is general agreement that the term ***risk factor*** means an exposure that is statistically related in some way to an outcome, e.g., smoking is a risk factor for periodontitis (Burt 2001). But beyond that broad generality is little agreement. There is uncertainty in the literature on whether a risk factor should be truly causal, i.e., a link in the etiological chain, or whether it can be more peripherally associated with an outcome. There also is uncertainty about what strength of association is needed for an issue to be called a risk factor for a disease and just how directly it needs to be associated with the outcome. Also, there is disagreement over whether a risk factor is immutable, like race or gender, or whether it is something that can be modified. Last agrees that the term *risk factor* is rather loosely used, and these definitions still leave important issues unanswered. In an effort to clarify this area, Beck has listed a definition (Beck 1998) that was adopted for the World Workshop on Periodontics in 1996 as " an environmental, behavioral, or biologic factor confirmed by temporal sequence, usually in longitudinal studies, which if present directly increases the probability of a disease occurring, and if absent or removed reduces the probability. Risk factors are part of the causal chain, or expose the host to the causal chain. Once disease occurs, removal of a risk factor may not result in a cure." This definition is longer than that given by Last, but is more specific according to Burt (Burt 2001) and he summarizes that he key contributions from this definition are: a) the emphasis on the temporal sequence of exposure before outcome; b) the acceptance that a risk factor is part of the causal chain; and c) the acceptance that risk factors are involved in disease onset, not necessarily in its future progression or resolution.

According to Page & Beck in their article published in International Dental Journal in 1997 (Page & Beck 1997); ***Assessment of risk for periodontitis*** was still in its infancy. Nevertheless, they are of the opinion that a sufficient amount of dependable information exists to begin using risk assessment in the day to day practice of dentistry. Their aim was to summarize existing information about risks for periodontitis in a manner that is useful to practitioners. Their study identified principal risk factors for moderate to severe periodontitis which included cigarette smoking, advancing age, diabetes mellitus and certain other systemic conditions. These include, osteoporosis and HIV infection and conditions such as irradiation and immunosuppressive drugs that interfere with normal host defenses, specific pathogenic bacteria in the sub gingival flora, microbial deposits and poor oral hygiene status, bleeding on probing, previous disease experience and severity, and inheritance. Some risks such as pathogenic bacteria in the sub gingival flora were strongly linked to causation of the disease while others such as bleeding on probing may indicate enhanced risk for future disease but were not known to be involved in causation and still others such as advancing age may be background factors that enhance susceptibility. While some risks such as cigarette smoking could be modified to lower the level of risk, others such as ageing were found to be immutable and couldn't be modified but needed to be considered in the overall risk assessment. A projected goal of periodontal diagnosis, treatment planning and therapy was purported to be to lower risk for future periodontal deterioration to the maximal extent.

In other studies by Page et al (Page Martin et al. 2003), Persson et al (Persson Mancl et al. 2003) and Sandberg et al (Sandberg & Fors 2007); the risk assessment of dental disease were discussed and ***computerized risk assessment*** was found to be better in comparison even with the judgment of experienced senior dental specialists. Risk assessment consists of recognizing that factors enhancing risk are present in a given case, and making subjective judgments as to the magnitude of their role in the disease process. In two separate studies by Persson et al (Persson Attstrom et al. 2003) (Persson Mancl et al. 2003) there is evidence that risk assessments based on subjective expert dentist and periodontist opinion vary too greatly to be useful in clinical periodontal decision making.

Dental Medicine International Inc., Mount Vernon, WA, USA have developed a computer-based tool, the ***Periodontal Risk Calculator*** (PRC), that quantifies risk and predicts periodontal deterioration (Page Krall et al. 2002). PreViser® Corporation has improved upon this tool recently to launch their new software called Oral Health Information Suite™ (Page Martin et al. 2005). According to Page et al (Page Martin et al. 2003; Page Martin et al. 2004), The PRC calculates risk for initiation of periodontal disease in healthy patients and the risk of disease progression in already affected subjects. The system evaluates certain factors as potential risk factors for disease and is based on algorithms that assign relative weights to the various known risks that enhance susceptibility for periodontitis. It determines the level of risk on a scale of 1–5 and generates suggested treatment options to guide the clinician and patient toward a health-care strategy based on risk reduction. The calculation of risk involves mathematical algorithms that use nine factors including: patient's age, smoking history, diagnosis of diabetes, history of periodontal surgery, pocket depths, furcation involvements, restorations or calculus below the gingival margin, radiographic bone height, and vertical bone lesions. It's predictive algorithm was validated using an existing database of periodontal patients. All these determinants factor into a risk score on a scale of one to five for periodontal deterioration for each individual.

INFORMATION REQUIRED BY (PRC) FOR DETERMINATION OF RISK SCORES
PRC : Periodontal Risk Calculator - (Page Krall et al. 2002)

Patient Age	Bleeding on Probing
Smoking History	Restorations Below the Gingival Margin
Diabetes Diagnosis	Root Calculus
History of Periodontal Surgery	Radiographic Bone Height
Pocket Depth	Furcation Involvements
Vertical Bone Lesions	

The use of PRC in the practice setting and suggested treatment options over time could lead to more uniform decision-making about periodontitis. They propound that if long-term studies support the promising initial results of

PRC's accuracy, this tool could have positive influence on the reduction in disease incidence, improved oral health, reduction in extensive treatment needs, and reduction in cost of care.

In their article in Compendium of Continuing Education In Dentistry published in 2005; Page, Martin & Loeb perceives that the cost of health care is increasing rapidly to necessitate a transition from the "repair" to a "wellness" model of oral health care that minimizes the occurrence of disease and the need for complex treatment may reduce costs and improve oral health. According to them; quantification of risk is essential for successful use of the wellness model and subjective risk assessment by expert clinicians is supposed to be too variable to be useful in clinical decision making. However, they are of the opinion that user-friendly Internet-based technology has been developed that provides a consistently accurate and valid quantified risk assessment for periodontitis, as well as a quantified measure of disease severity and extent. The numeric information helps clinicians and patients make diagnoses and generate individual, needs-based treatment plans. This technology enables successful application of the wellness model of care in day-to-day dental practice. Use of the wellness model may result in more uniform and accurate periodontal clinical decision making, improved oral health, less need for complex periodontal therapy, lower oral health care costs, and improved clinician productivity and income.

Persson and his co-workers in 2003 (Persson Mancl et al. 2003) conducted a study to compare risk scores assigned by subjective expert clinician opinion with quantitative scores generated for the same subjects using the Periodontal Risk Calculator, or PRC. The authors assembled a group of 107 subjects and performed standard periodontal examinations. They entered the resulting information into the PRC and calculated risk scores for two and four years, assuming no treatment would be performed. Using the same subject records, three groups of expert clinicians assigned risk scores for years 2 and 4. The authors analyzed the data to reveal the extent of inter evaluator variation and the level of agreement between expert clinician scores and PRC scores. The results showed that the extent of variation among scores assigned by individual expert clinicians was greater than the authors had expected. Expert clinicians consistently assigned more subjects to PRC risk group 2 and fewer to risk group 5 than did the PRC. The authors observed very high heterogeneity in the risk scores expert clinicians assigned to patients in each of the PRC-assigned groups. Thus, expert clinicians varied greatly in evaluating risk and, relative to the PRC, they appeared to underestimate periodontitis risk, especially for high-risk patients. Their observations suggest that use of risk scores generated for individual patients by subjective expert clinician opinion about risk in periodontal clinical decision making could result in the misapplication of treatment for some patients and support the use of an objective tool such as the PRC. Use of the PRC over time may be expected to result in more uniform and accurate periodontal clinical decision making, improved oral health, reduction in the need for complex therapy and reduction in health care costs.

In a ground breaking study of practical applications of ***Artificial Neural Networks in Oral Science*** by Speight and his co-workers in 1995 (Speight Elliott et al. 1995); artificial Intelligence involving the use of neural networks can be used effectively to identify subjects at risk of oral cancer and pre cancerous lesions. According to them; Artificial Intelligence is being used increasingly as an aid to diagnosis in medicine & the purpose of this study was to evaluate the ability of a neural network to predict the likelihood of an individual having a malignant or potentially malignant oral lesion based on knowledge of their risk habits. Performance of the network was compared with a group of dental screeners in a screening program involving 2027 adults. The screening performance was measured in terms of sensitivity, specificity and likelihood ratios. All subjects were examined independently by a dental screener and a specialist, who provided a definitive diagnosis, or 'gold standard', for each individual. All subjects also completed an interview questionnaire regarding personal details, dental attendance and smoking and drinking habits. The neural network was trained on 1662 of the screened population using ten input variables derived from the questionnaire along with the outcome of the specialist's diagnosis. Following training, the network was asked to classify the remaining unseen proportion (365 individuals) of the screened population as positive or negative for the presence of cancer or precancer. The overall sensitivity and specificity of the dentists were 0.74 [95% confidence interval (CI), 0.62-0.86] and 0.99 (95% CI, 0.985-0.994) respectively compared with 0.80 (99% CI, 0.55-1.00) and 0.77 (95% CI, 0.73-0.81) for the neural network. In view of the potential costs involved in implementing a screening program, they propose that neural networks may be of value for the identification of individuals with a high risk of oral cancer or precancer for further clinical examination or health education. A similar study by Zhizhina et al (Zhizhina Prokhonchukov et al. 1998) titled "A computerized automated system for the differential diagnosis and treatment of oral mucosal diseases" discusses a computerized system for identifying the classifiers and recognizes patterns for differential diagnosis and proposes treatment strategies. Similarly, Suhr etal in an article published in year 2000 in the International journal of oral and maxillofacial surgery titled "Optical biopsy systems for the diagnosis and monitoring of superficial cancer and precancer"; discusses the usefulness of optical biopsy systems utilizing similar algorithms to diagnose and monitor cancerous and pre cancerous lesions.

In another study by Brickley et al in 1996 (Brickley Cowpe et al. 1996) the performance of a computer simulated neural network trained to categorize normal, premalignant and malignant oral smears were assessed. The accurate detection of malignant neoplasms whilst they are still small is recognized as one of the main factors increasing chances of survival. Neural networks have many biomedical applications and they have been applied to neoplasia but their use in oral pathology has only recently been documented. The objectives of this particular study were to train networks to discriminate between normal and dysplastic mucosa. Each network was trained by back propagation, internal cross validation and tested on additional data. The data were derived by analyzing 348 intra-oral smears and included mean nuclear and mean cytoplasmic areas of the smears measured by image analysis. A neural network differentiated between normal/non-dysplastic mucosa and dysplastic/malignant mucosa (specificity 0.82, sensitivity 0.76). These early results suggest that integrating neural networks and image analysis, as well as investigating additional criteria, could enhance automation and accuracy of smear techniques in diagnosing oral malignancy.

In the study by Salvi et al (Salvi Dazzi et al. 2002) titled "Classification and Prediction of the Progression of Thyroid-associated Ophthalmopathy by an Artificial Neural Network", published by the National Center for Biotechnology Information; the use of neural networks to diagnose and predict the progression of eye problems associated with thyroid disease was examined. It was determined that with appropriate information and a learning process, the neural network was able to correctly identify almost 80% of eyes as being positive or negative for thyroid associated Ophthalmopathy (TAO). The network was also able to correctly predict the progression of the disease in almost 70% of the patients.

Neural networks are useful in predicting risk associated with medical and dental conditions owing to the multilayer nature of algorithms with interacting nodes and standard error correction by ***backward propagation of Multi Layer Perceptron neural networks.*** The back Propagation Algorithm proposed by Rumelhart, Hinton and Williams in 1988 (Rumelhart Hinton et al. 1988) essentially eliminates the error inherent in the comparison between the output calculations and the desired values.

The Multi layer Feed forward Neural Networks are influenced by;

1. The learning algorithm and number of iterations - This determines how good the error on the training set is minimized.

2. The number of learning samples - This determines how good the training samples represent the actual function.

3. The number of hidden units - This determines the 'expressive power' of the network. For 'smooth' functions only a few number of hidden units are needed, for wildly fluctuating functions more hidden units will be needed.

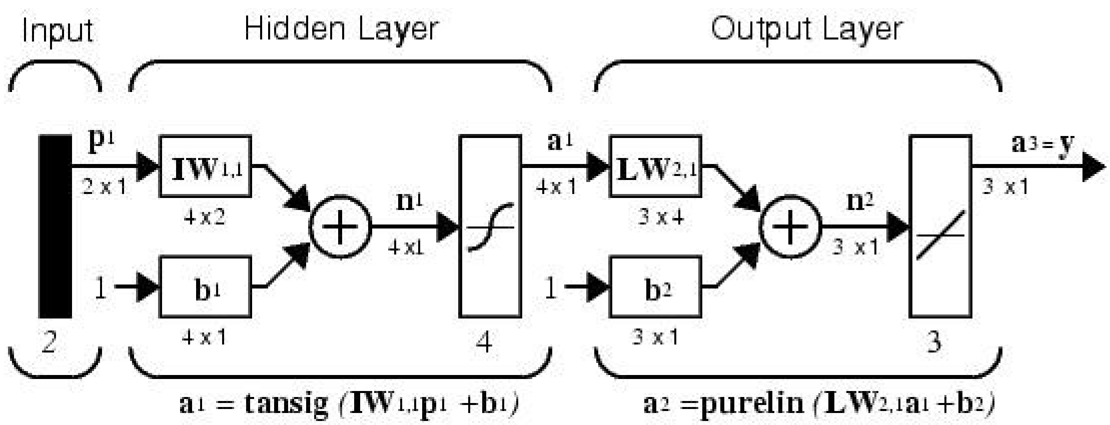
Artificial neural networks have developed from generalized neural biological principles (Krieger 2008). McCulloch et al (McCulloch & Pitts 1943)proposed the neuron as a binary threshing device in discrete time.

Neurons are now known to be more complicated than this model having a graded, rather than threshold, response, operating in continuous time, and achieving nonlinear functions of inputs (Ripley 1994). Compared to computers However; neurons are rather slow, with a speed of about 100 meters/second. To compensate for this lack of speed, the human brain is highly distributed and massively parallel. As parallel processes go the human brain is unsurpassed.

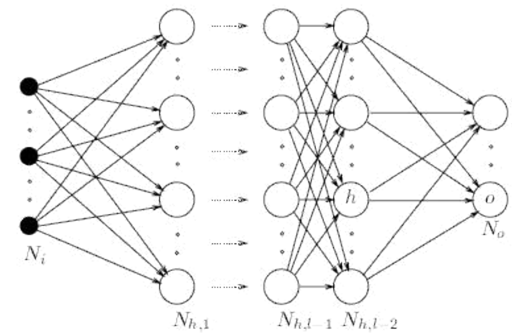
The pattern of connections between neurons proves to be an ideal model for the neural network's architecture (Fausett 1994). According to Fausett; Neural networks essentially comprise of three pieces: The Architecture or Model, The Learning Algorithm and The Activation functions.

Neural networks are programmed or trained to store, recognize, and associatively retrieve patterns or database entries; to solve combinatorial optimization problems; to filter noise from measurement data; to control ill defined problems. In summary, to estimate sampled functions when we do not know the form of the functions (Kosko 1992). It is precisely these two abilities namely, pattern recognition and function estimation which make Artificial Neural Networks (ANN) so prevalent a utility in classifying and estimation studies. As data sets grow to massive sizes, the need for automated processing becomes clear. With their "model-free" estimators and their dual nature, neural networks serve these purposes in a myriad of ways.

Minsky and Papert (Minsky & Papert 1969) showed in 1969 that a two layer feed-forward network can overcome many restrictions, but did not present a solution to the problem of how to adjust the weights from input to hidden units. An answer to this question was presented by Rumelhart et al in 1988 (Rumelhart Hinton et al. 1988). The central idea behind this solution is that the errors for the units of the hidden layer are determined by back-propagating the errors of the units of the output layer. For this reason, the method is often called the ***back-propagation learning rule.*** Back-propagation can also be considered as a generalization of the delta rule for non-linear activation functions and multilayer networks.



Multi-layer feed-forward networks have a layered structure. Each layer consists of units which receive their input from units from a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. The input units are merely 'fan-out' units; no processing takes place in these units. The activation of a hidden unit is a function of the weighted inputs plus a bias. The output of the hidden units is distributed over the next layer, until the last layer of hidden units.



A Multi Layer Network with „l" layers of units

Although back-propagation can be applied to networks with any number of layers, just as for networks with binary units, it has been shown by various researchers like (Hornik Stinchcombe et al. 1990); (Funahashi 1989); (Cybenko 1989) & (Hartman Keeler et al. 1990) that only one layer of hidden unit suffices to approximate any function with finitely many discontinuities to arbitrary precision, provided the activation functions of the hidden units are non-linear (the universal approximation theorem). In most applications a feed forward network with a single layer of hidden units is used with a sigmoid activation function for the units.

7. RESEARCH GAPS IDENTIFIED IN THE PROPOSED FIELD OF INVESTIGATION

From the analysis of critical issues inherent in the technologies currently implemented for data mining in medical and dental fields; some important factors can be identified. Most of the biomedical researchers are currently using normal linear regression and correlation algorithms as analyzing techniques to interpret the data obtained by pain staking research in biomedical fields especially dentistry; while properly trained neural network pattern algorithms for a particular problem can be used as a powerful tool to validate future research in similar areas with lesser number of subjects. *The difficulty in accurately describing future trends in dental disease progression and prediction using existing valuable data should be addressed to compensate for the lacunae existing in the dental research field.* To fulfill these deficiencies, there *is a need to create an appropriately trained pattern for classifying and risk prediction using intelligent neural network algorithms* which can be used as a standard tool for modeling future research projects.

8. OBJECTIVES OF THE PROPOSED STUDY

The proposed research work is *aimed at developing a custom neural network to predict periodontal disease risk by modifying the standard functions presently being used for Multiple Layer Perceptron method of neural network design* and also to discover new algorithms which can effectively represent the connections between the nodes in hidden layers to produce minimum standard error. The neural pattern developed will be tested using additional data to see how well the results are in correlation with the predicted values and we will try to construct a learning algorithm which can be used to improve the neural network with future predictions.

WORK-FLOW :

- The Dental data consisting of the variable parameters like Age, Sex, Diet, Bleeding on Probing, Periodontal Attachment Loss, Radiographic Bone Loss, Family History of Periodontitis, Debris Index, Calculus Index, and other intra oral parameters relevant to the study in question would be recorded and tabulated from the Case files. The Systemic parameters like Blood sugar levels and Blood Pressure measurements with relevant laboratory values would be tabulated and integrated into the study to be added to the input arms of the neural network.
- The data would be validated into the system and matrices would be constructed.
- Variables are defined for the input and target parameters.
- The network is going to be designed initially with a standard topography and the results would be analyzed.

- Algorithms would be tested using Simulink® in a virtual simulated environment
- The modeled neural network pattern would be trained with additional data and learning algorithms improved.
- The trained network would be tested with the rest of the samples assigned to the category and the code would be optimized for the errors displayed.
- Final modeling of neural network would be done and code optimized.

9. RESEARCH METHODOLOGY

A. HYPOTHESIS TO BE TESTED

Multilayer Perceptron Feed Forward Neural Networks with improved back propagation and process function algorithms can effectively be trained to simulate and reproduce a real life periodontal risk assessment problem; where the layered interaction between Processing Elements in the network may accurately simulate the neuronal network in an experienced clinician to predict the possibility of a particular periodontal disease pattern emerging from input data received by examining the patient in future scenarios.

B. SOURCES OF INFORMATION

- PUBMED – NLM
- WEB OF SCIENCE
- NATIONAL LIBRARY OF MEDICINE
- IEEE EXPLORE
- PRINCETON UNIVERSITY
- MIT
- LIBRARY OF CONGRESS
- LIBRARIES AUSTRALIA
- CALIFORNIA STATE LIBRARY
- BIBLIOCENTER
- UNIVERSITY OF EDINBURGH

C. TOOLS & TECHNIQUES OF RESEARCH

MATERIALS:

(1) Retrospective periodontal patient data collected from the digital archives maintained by the Dental Wing of Pacific University, Pacific Hills, Debari, Udaipur, India

(2) MATLAB® version 2008a Professional Edition

(3) Neural Network Toolbox extension version 6.0 of MATLAB®

(4) Neurosolutions® program version 5.0 Developers Edition

(5) Microsoft® Visual Studio 2005 & 2008

(6) SPSS v17.00

PROPOSED STUDY DESIGN

The study would be conducted in the dental wing of Pacific University, Pacific Hills, Debari, Udaipur, India; where archived data of a total of 600 subjects would be assessed to record the various subjective parameters like Age, Sex, Diet, Family History of Periodontitis, Previous History of Periodontal Treatment, Previous & Present History of Smoking, Pan Chewing and the objective parameters of Bleeding On Probing, Debris Index, Calculus Index, Periodontal Probing Depth, Radiographic Bone Loss, Subgingival Restorations, Furcation Involvements & The total number of Angular Infra Bony Defects. The Laboratory Investigations for Elevated Blood Sugar Levels and Blood Pressure would also be recorded under variable parameters. The study would be afloat for a minimum period of 24 months during which a comprehensive cross sectional sampling method would be used to collect the variable data to be fed into the input arms of the designed Multi layer Perceptron model of Feed Forward Propagation Artificial Neural Network. The recorded prognosis assessments for these subjects would be used to design, train and test the neural network, and the neural network training would be optimized in such a way that the testing phase produces immediate convergence with expected accuracy and for this purpose the neural network would be designed in such a way as to minimize the maximum error to reach the observed parameters with reduced amount of time; and the network would be trained with a sufficient number of samples to make the hidden nodes viable to be tested for real life scenarios.

The neural network algorithm would be adjusted in such a way that the back propagation training source failure factors of network paralysis and local minima are virtually eliminated for the network to converge at a faster speed with greater reliability for future real life applications. We would be using a comparatively large number of samples to reduce sampling error and the number of epochs used will be minimum of 1000 to enhance the spectrum of learning vectors gained during each iterations. The other factors such as synaptic weights, vector angles at each nodes and the number of hidden layers will be adjusted dynamically in the testing network algorithm using MATLAB and Neurosolutions to get a standard error reduction optimized for accurate risk prediction. The resulting final neural network algorithm would be coded and could be exported into a Graphical User Interface to be used for MATLAB, C/C++ future projects.

In order to study construct and test an artificial Neural Network Model and to use the learning capabilities of a neural network using the proposed algorithm, we would be using the Multi layer Perceptron model of Feed Forward Propagation with back propagation algorithm to minimize standard error between the output and the desired value. For this purpose we would be using periodontal examination sample data of 600 subjects from the dental archive repository of patients reporting to the outpatient section of Pacific Dental College & Hospital, Pacific University, Udaipur, India.

The independent variables for input like Age, Sex, Diet, Family History of Periodontitis, Previous History of Periodontal Treatment, Previous & Present History of Smoking, Pan Chewing, Bleeding On Probing, Debris Index, Calculus Index, Periodontal Probing Depth, Radiographic Bone Loss, Subgingival Restorations, Furcation Involvements, Number of Angular Infra Bony Defects and values for Diabetes & Hypertension would be distributed on the input nodes of the neural network and the desired or prediction node would be assigned the desired variable namely the risk assessment at the time of diagnosis classified according to it's severity into five categories ranging from Grade 1 to 5 similar to the PRC tool developed by Page et al (Page Krall et al. 2002).

Our study would be incorporating more periodontal risk parameters namely Pan Chewing, Debris Index, Calculus Index, Diet & Family History of Periodontitis. Pan chewing is a deleterious habit particular to this part of the world and we expect to get better geographically specific mathematical custom solutions which would accurately interpret the collected data to give us a more specific periodontal risk evaluation concerning subjects in this particular region with lower economic burden compared with the present custom PRC solution offered by PreViser® at an annual subscription starting at \$2960. Page et al conspicuously omitted some of the significant parameters like present Oral Hygiene Status (Corraini Baelum et al. 2008) (Ainamo & Ainamo 1996) and Family History of Periodontitis; while these factors are proved otherwise as suspected risk factors and in fact; Page et al (Page Krall et al. 2002) mentions in his article the importance of host response by stating that "The idea that host factors are a major determinant of disease onset and progression and that risk and susceptibility vary greatly from one person to another had not been conceived".

The pilot study diagram would be constructed with half of the sample data consisting of 100 subjects and 100 samples would be used to train the network with multiple iterations of 1000 cycles to determine the ideal weight of nodes and number of hidden layers needed for a minimum 95% accuracy. The test samples in the pilot study would consist of the remaining 100 samples and the test sample data would be fed into the trained network to test the accuracy of training and modifications would be done as and where appropriate. The study would focus on optimizing the designed neural network to accurately analyze and predict the severity of disease associated with the analyzed common risk factors proposed as the variables in the input arms of the optimized neural network.

The designing, training and optimizing of the custom neural network would take much of the time of the present study; and we hope to be finally able to reach upon an agreed system in which the variables would be sufficiently balanced with optimal hidden layers and with minimum number of nodes.

10. BIBLIOGRAPHY

Ainamo J, Ainamo A (1996) Risk assessment of recurrence of disease during supportive periodontal care. Epidemiological considerations. *J Clin Periodontol* **23**(3 Pt 2)**,** 232-239.

Beck JD (1998) Risk revisited. *Community Dent Oral Epidemiol* **26**(4)**,** 220-225.

Brickley MR, Cowpe JG, Shepherd JP (1996) Performance of a computer simulated neural network trained to categorise normal, premalignant and malignant oral smears. *J Oral Pathol Med* **25**(8)**,** 424-428.

Brickley MR, Shepherd JP, Armstrong RA (1998) Neural networks: a new technique for development of decision support systems in dentistry. *J Dent* **26**(4)**,** 305-309.

Burt BA (2001) Definitions of risk. *J Dent Educ* **65**(10)**,** 1007-1008.

Corraini P, Baelum V, Pannuti CM, Pustiglioni AN, Romito GA, Pustiglioni FE (2008) Risk indicators for increased probing depth in an isolated population in Brazil. *J Periodontol* **79**(9)**,** 1726-1734.

Cybenko G (1989) Approximation by superpositions of a sigmoidal function. *Mathematics of Control, Signals, and Systems (MCSS)* **2**(4)**,** 303-314.

Fausett L (1994) *Fundamentals of neural networks: architectures, algorithms, and applications*: Prentice Hall Englewood Cliffs, NJ.

Funahashi K (1989) On the approximate realization of continuous mappings by neural networks. *Neural Networks* **2**(3)**,** 183-192.

Gniadecka M, Philipsen PA, Sigurdsson S *et al.* (2004) Melanoma diagnosis by Raman spectroscopy and neural networks: structure alterations in proteins and lipids in intact cancer tissue. *J Invest Dermatol* **122**(2)**,** 443-449.

Hartman E, Keeler J, Kowalski J (1990) Layered neural networks with Gaussian hidden units as universal approximations. *Neural computation* **2**(2)**,** 210-215.

Hornik K, Stinchcombe M, White H (1990) Universal approximation of an unknown mapping and its derivatives using multilayer feedforward networks. *Neural Networks* **3**(5)**,** 551-560.

Kosko B (1992) *Neural networks and fuzzy systems: a dynamical systems approach to machine intelligence*: Prentice-Hall, Inc. Upper Saddle River, NJ, USA.

Krieger C (2008) Neural Networks in Data Mining.

Last J (2001) *A dictionary of epidemiology*: Oxford University Press, USA.

McCulloch W, Pitts W (1943) A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biology* **5**(4)**,** 115-133.

Minsky M, Papert S (1969) Perceptions. *MIT Press, Cambridge, MA. The impact of strategic planning on the competitiveness, performance and* *effectiveness of bank branches: a neural network analysis International Journal of Bank Marketing* **20**(3)**,** 2002.

Page RC, Beck JD (1997) Risk assessment for periodontal diseases. *Int Dent J* **47**(2)**,** 61-87.

Page RC, Krall EA, Martin J, Mancl L, Garcia RI (2002) Validity and accuracy of a risk calculator in predicting periodontal disease. *J Am Dent Assoc* **133**(5)**,** 569-576.

Page RC, Martin J, Krall EA, Mancl L, Garcia R (2003) Longitudinal validation of a risk calculator for periodontal disease. *J Clin Periodontol* **30**(9)**,** 819-827.

Page RC, Martin JA, Loeb CF (2004) Use of risk assessment in attaining and maintaining oral health. *Compend Contin Educ Dent* **25**(9)**,** 657-660, 663-656, 669; quiz 670.

Page RC, Martin JA, Loeb CF (2005) The Oral Health Information Suite (OHIS): its use in the management of periodontal disease. *J Dent Educ* **69**(5)**,** 509-520.

Persson GR, Attstrom R, Lang NP, Page RC (2003) Perceived risk of deteriorating periodontal conditions. *J Clin Periodontol* **30**(11)**,** 982-989.

Persson GR, Mancl LA, Martin J, Page RC (2003) Assessing periodontal disease risk: a comparison of clinicians' assessment versus a computerized tool. *J Am Dent Assoc* **134**(5)**,** 575-582.

Ripley B (1994) [Neural Networks: A Review from Statistical Perspective]: Comment. *Statistical Science* **9**(1), 45-48.

Rumelhart DE, Hinton GE, Williams RJ (1988) Learning representations by back-propagating errors. *Neurocomputing: foundations of research*, pp. 696-699: MIT Press.

Salvi M, Dazzi D, Pellistri I, Neri F, Wall JR (2002) Classification and prediction of the progression of thyroid-associated ophthalmopathy by an artificial neural network. *Ophthalmology* **109**(9), 1703-1708.

Sandberg HC, Fors UG (2007) The HIDEP model--a straightforward dental health care model for prevention-based practice management. *Swed Dent J* **31**(4), 171-179.

Speight PM, Elliott AE, Jullien JA, Downer MC, Zakzrewska JM (1995) The use of artificial intelligence to identify people at risk of oral cancer and precancer. *Br Dent J* **179**(10), 382-387.

Zhizhina N, Prokhonchukov A, Rabinovich I, PelkovskiÄ V (1998) A computerized automated system for the differential diagnosis and treatment of oral mucosal diseases. *Stomatologiia* **77**(1), 55.

Rajesh 19/08/2010

Signature of the Candidate with Date

Outline Approved

LKM 19-8-2010

Name & signature of supervisor with date & seal

Principal
PACIFIC DENTAL COLLEGE
UDAIPUR