Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 4, Issue. 12, December 2015, pg.313 – 323

An Innovative and Automatic Lung and Oral Cancer Classification Using Soft Computing Techniques

Mr. Tanupriya Choudhury[1], Prof.(Dr.) Vivek Kumar[2], Dr. Darshika Nigam[3]

[1]Research Scholar (CSE), Jagannath University, Jaipur, India
[2]Principal, Delhi College of Technology and Management, Palwal, India
[3]Department of BioChemistry, SLS, Dr. B.R. Ambedker University, Agra, India

[1] tanupriya1986@gmail.com; [2] profvivekkumar@gmail.com; [3] drdarshikanigam@rediffmail.com

Abstract: ***Lung and Oral Cancer are the most common diseases found in the majority of the populations in recent years. Medical diagnosis is colossally crucial but intricate task that should be accomplished exactly and proficiently. Although momentous progress has been made in the diagnosis and treatment of these diseases, further investigation is still desired. Soft Computing & DM techniques is the use of algorithms to mine the information and designs derived by the knowledge discovery from databases. Classification maps data into predefined groups or classes .The prognosis and diagnosis of cancer has been a challenging research problem for many researchers. The main objective of this proposed work is to compare the performance analysis of various soft computing and DM techniques to identify the Lung & Oral cancer prediction. This work employs different kinds of neural network classifiers. It confirms that the MLP networks produce more specific, accurate results compared to other techniques for Lung and Oral Cancer datasets.***

I. INTRODUCTION

In classification learning, the learning scheme is depicted with a set of classified examples from which it is expected to learn a way of classifying unseen examples. While in association learning any association among features is sought not just ones that predict a particular class value. Whereas in clustering, groups of examples that belong together are sought.

Lung cancer was a very rare disease at the start of the 20th century. But now exposure to new contributory agents and also due to the increasing lifespan of people, have contributed to make lung cancer a deadly disease of the 21st century. It remains the foremost cause of cancer deaths worldwide, with 1.4 million deaths in 2014. Even though a wide list of risk factors has been well considered, and lifestyle changes have

occurred regarding tobacco consumption, particularly in men in Western Europe, lung cancer remains a huge health problem as a result of environmental changes and pollution.
The relevant International Classification of Disease (ICD) codes (used to code and classify mortality data from death certificates) are ICD-10 C33 (neoplasm of the trachea) and ICD-10 C34 (neoplasm of bronchus and lung)[21].
Research has intended to classify patients with early- stage disease in the hope of improving persistence and developing individualized therapies for patients with advanced disease. Oral cancer is highly related to the sex of the patient, with males face double the risk of being diagnosed with oral cancer than females.
The known risks associated with Oral and Lung cancer include smoking, alcohol consumption, tobacco use, and betel quid chewing[32].
Besides risks factors, there are other factors associated with oral cancer such as viral infection, diet, genetic factors and poor oral hygiene (Jefferies & Foulkes, 2001; Reichart, 2001; Sunnitha & Gabrial, 2004; Mehrotra & Yadav, 2006). The WHO(World Health Organization) expects a worldwide rise in oral cancer incidence in the next few decades due to high smoking dominance and increasing cases of unfit diet. Almost two-thirds of oral cancer occurs in developing countries like South East Asia, India and Brazil and this geographic variation probably reflects the occurrence of specific environmental influences and risk habits (Oliveira et al.,2008).

Sr. No	Author & Year Published	Methodology	Datasets	Performance
1	Wang Tao, Lv Jianping and Liu Bingxin, [2014]	RBFN, LLS, gradient descent	5,000 valid data as samples	95.32% accuracy
2	Yongjun WU, Na Wang, Hongsheng ZHANG Lijuan Qin Zhen YAN and Yiming WU [2015]	Computer Aided Diagnostic Scheme - CT and ANN	CT Images of Pulmonary Nodules - 117, (Benign -58 and Malignant -59)	ANN Illustrate - 96.6 % Accuracy & Logistic Regression - 84.6%
3	Fatma Taher & Rachid Sammouda [2011]	HNN & FCM	100 sputum color images	HNN segmentation results were more accurate than FCM
4	Jung Hun Oh, Jeffrey Craft Rawan Al-Lozi and Manushka Vaidya [2010]	Graphical Bayesian Network Framework	Physical Variables Dataset (Biomarker Proteins - 4)	Accuracy - 87.78%
5	Ankit Agrawal and Alok Choudhary [2015]	Association rule mining & hotspots	A subset of 13 patient attributes from the SEER data	Survival time of patients increased.
6	Tadashi Kondo, Junji Ueno and Shoichiro Takao [2012]	GMDH	medical images	Diagnosis efficiency can be improved.
7	S. Aravind Kumar, Dr. J. Ramesh, Dr. P. T. Vanathi and Dr. K. Gunavathi [2011]	Computer Aided Diagnosis, Segmentation Fuzzy Systems	Slice Images - 685 (Clinical Cases - 40)	Classification Accuracy - 90%
8	Hamada R. H. AI-Abs Brahim Belhaouari Samir Khaled Bashir Shaban and Suziah Sulaiman [2012]	Machine Learning Techniques	Chest Radiographs - 247 (Nodules Images - 154 and Normal Images - 93)	Classification Accuracy - 96%
9	Aminmohammad Roozgard, Samuel Cheng, and Hong Liu [2012]	kernel RX-algorithm	CT images from of size 512 x 512	Proved efficient.
10	Xiaozhou Li, Rong Wang and Ming Lei [2011]	Fluorescence Spectroscopy	36 serums	83.3% classification accuracy
11	Thessa T.J.P. Kockelkorn, Eva M. van Rikxoort, Jan	Computed tomography, lung	12 thoracic CT scans from lung	Useful when automatic

	C. Grutters and Bram van Ginneken [2010]	segmentation.	transplantation and ILD patients	segmentation methods fail.
12	Yongjun WU, Na Wang, Hongsheng ZHANG, Lijuan Qin, Zhen YAN, Yiming WU [2014]	CAD scheme of the CT and ANN	117 CT images of pulmonary nodules (58 benign and 59malignant)	ANN showed 96.6 % accuracy & Logistic Regression gave 84.6% accuracy.
13	Peng Gang, Yang Xiong and Liu Li [2011]	Immune Algorithm	Medical Images of Chest X-ray	Efficient for detecting suspected lung cancer
14	Jia Tong, Wei Ying and Wu Cheng Dong [2010]	Lung Vessel Segmentation Computer Aided Diagnostic	Thoracic CT Scans - 90	Total Detection Rate - 85%
15	Thessa T.J.P. Kockelkorn Eva M. Van Rikxoort Jan C. Grutters and Bram van Ginneken [2010]	Lung Segmentation and Computed Tomography	Thoracic CT Scans (Lung Transplantation and ILD Patients) - 12	When Automatic Segmentation Methods Fail – Useful
16	Jung Hun Oh, Jeffrey Craft Rawan Al-Lozi and Manushka Vaidya [2010]	Graphical Bayesian Network Framework	Physical Variables Dataset (Biomarker Proteins - 4)	Accuracy - 87.78%

Table 1 : Different Methods Performance Counselled for Lung Cancer Diagnosis

Oral Cancer in India: In the Indian subcontinent oral cancer has been a major disease, where it ranks among the top three types of cancer in the country. Age adjusted rates of oral cancer in India is very high, that is, 21 per 125,000 population and accounts for over 32% of all cancers in the country. The variation in incidence and pattern of the disease can be attributed to the combined effect of ageing of the population, as well as regional differences in the prevalence of disease-specific risk factors.

Oral cancer starts in the oral cavity. The oral cavity includes the lips, the inside lining of the lips and cheeks (buccal mucosa), the gums, the teeth, the floor of the mouth below the tongue, the front two-thirds of the tongue, the bony roof of the mouth (hard palate), and the area behind the wisdom teeth (retromolar trigone). Cancer cells can widely spread to other neighboring parts of the lungs, the neck or elsewhere in the body. A common metastasis occurs in the lymph nodes of the neck through the lymphatic system which helps the cancer cells to spread over. Although nowadays, the rigorous improvements in treatment protocols of cancer have attained high rates of successful disease disappearance, there is a vital stage for the disease evolvement after the treatment called remission. During this stage there is no clinical, laboratory or imaging evidence of the neoplastic mass and the patient is considered cancer free.

But, even at this point some “invisible” particles of disease might be emerging out, which leads to a potential spread or metastasis of the disease. Specifically, in terms of oral cancer, locoregional reoccurrence rates after the disease has reached remission have been reported in the range of 26-50%; such high figures can be justified given the deeply infiltrative nature of these tumors, as well as, the significant potential for occult neck metastasis.

The rates of reoccurrence for oral cancer are quite high and they also suffer from poor level of prognosis, which can be partly attributed to histologically adverse features. Moreover, patients suffering from oral cavity cancer have to deal with the impact of the disease and its treatment on their appearance (physically) and on their ability to eat and speak, and subsequently with a significant decrease of the life quality. Hence, pre-detection of reoccurrence might prove very helpful. Currently implemented methods aiming to predict oral cancer reoccurrence after the disease has reached remission, have reported quite inadequate results. Although several factors have been associated with the reoccurrence of oral cancer, such as site, age and stage of the primary tumor as well as histological features, they have not been studied altogether in a collective study.

II. SOFT COMPUTING & DATA MINING METHODS

Soft Computing is a branch of artificial computational intelligence that employs a variety of statistical, probabilistic and optimization techniques that allows computers to "learn" from past examples and to detect hard-to-discern patterns from large, noisy or complex data sets. This capability is particularly well-suited to medical applications, especially those that depend on complex proteomic and genomic measurements.[17]

As a result, computational intelligence is frequently used in cancer diagnosis and detection. More recently soft computing has been applied to cancer prognosis and prediction. A number of trends are there, including a growing dependence on protein biomarkers and microarray data, a strong bias towards applications in prostate and breast cancer, and a heavy reliance on "older" technologies such artificial neural networks (ANNs) instead of more recently developed or more easily interpretable soft computing techniques.[23]

A number of published studies also appear to lack an appropriate level of validation or testing. Among the better designed and validated studies it is clear that soft computing techniques can be used to substantially (15– 25%) improve the accuracy of predicting cancer susceptibility, recurrence and mortality. At a more fundamental level, it is also evident that computational intelligence is also helping to improve basic understanding of cancer development and progression.

The techniques of soft computing may include neural network, fuzzy set theory, genetic algorithm and simulated annealing etc. The below stated table describes the strength of the soft computing techniques.

Table 1: Various Methodologies For Soft Computing

S.Nm.	Methodology	Strength
1	Neural Networks	Learning & Adaption
2	Fuzzy Logic and fuzzy set theory	Knowledge representation via fuzzy if-then rules
3	Genetic algorithm and simulated annealing	Systematic random search
4	Conventional AI	Symbolic manipulation

Table 2: Various Soft Computing Techniques In Diagnostics Of Diseases [30][31][32]

Sl. No.	SC Techniques used	Diseases cure/detection/recognition
1	Fuzzy logic	Neural system disorder
2	Medical imaging (bio inspired soft computing)	Cancer, arteriosclerosis, epilepsy, Alzheimer, Parkinson
3	Object-oriented expert system	Diagnosis of fungal diseases of date palm
4	Decision support systems	Diagnosis of disease states and corresponding herbal prescriptions
5	Neural networks, image processing	Oral cysts
6	Artificial neural network	Neonatal disease diagnosis
7	Decision support system	Congenital heart disease diagnosis based on signs and symptoms
8	Fuzzy knowledge base	Glaucoma monitoring
9	Clustering techniques	To distinguish the data set to two primary clusters i.e. diseased and disease free
10	Classification techniques	To classify a sample at first as diseased or free from disease and subsequently if diseased then particular type of the disease

III. DISEASE DETECTION MODULE (LUNG AND ORAL DETECTION)

#no	Attribute	Values
1	Record Number	Continuous
2	Survival Time	Continuous
3	Censored	Binary
4	Medical Condition	Continuous
5	Age	Continuous
6	Time_Diagram Study	Continuous
7	Tumour type	Binary
8	Treatment	Binary
9	Type of Surgery	Binary
10	Cancer Grade	Continuous
11	Radiation Therapy	Binary
12	Cancer Stage	Continuous
13	Diagnostic Confirmation	Binary
14	EGFR	Continuous
15	Bone Age	Continuous
16	Average BP	Continuous
17	Distance to Margin	Continuous
18	Heart Rate	Continuous
19	Platelet Count	Continuous
20	Weight	Continuous
21	Lv-X3	Continuous

Table 3 : Lung Cancer Attributes

#no	Attribute	Values
1	Patient_id	Continuous
2	Trt	Continuous
3	Age	Continuous
4	Weights	Continuous
5	Bone_invasion	Binary
6	Totalcin	Continuous
7	Totalcw	Continuous
8	Totalcw4	Continuous
9	Totalcw6	Continuous
10	Stage	Continuous
11	Ethnic_origin	Binary
12	Primary_tumor	Binary
13	Site_radiotherapytreate	Binary
14	Oncologist	Continuous
15	Diagnosis_status	Binary
16	Treatment_offered	Binary
17	Treatment_modality	Continuous
18	Tumor_previoustrement	Binary
19	Performance_statuspresent	Binary
20	Laterality	Continuous
21	Survival Time	Continuous

Table 4: Oral Cancer Attributes

Multilayer Perceptron (Mlp):

An MLP is a network of simple *neurons* called *perceptron.* The perceptron computes a single *output* from multiple real-valued *inputs* by making a linear combination according to its input *weights* and then probably putting the output through some nonlinear activation function.

$$y = \varphi(\sum_{i=1}^{n} w_i x_i + b) = \varphi(\mathbf{w}^T \mathbf{x} + b)$$

Equation 1

Where w- vector of weights, , b- bias, x- vector of Inputs and φ Activation Function

Logistic Sigmoid

$$1/(1+e^{-x})$$

Equation 2

The calculations done by such a feed forward network with a one hidden layer with not a linear activation functions and a linear output layer can be written mathematically as

$$\mathbf{x} = \mathbf{f}(\mathbf{s}) = \mathbf{B}\boldsymbol{\varphi}(\mathbf{A}\mathbf{s} + \mathbf{a}) + \mathbf{b}$$

Equation 3

Where $\mathbf{s}$ is a vector of inputs and $\mathbf{x}$ a vector of outputs. $\mathbf{A}$ is the matrix of weight of the first layer, $\mathbf{a}$ is the bias vector of the 1st layer. $\mathbf{B}$ and $\mathbf{b}$ are, respectively, the matrix of weight and the bias vector of the second layer. The function $\boldsymbol{\varphi}$ denotes an element wise nonlinearity.

Squared Reconstruction Error

$$\sum_t ||\mathbf{f}(\mathbf{s}(t)) - \mathbf{x}(t)||^2$$

Equation 4

Using the Simple logistic algorithm and MLP the lung and oral cancer has been further divided for better prediction and also a survey of genetic expression of microarray technology has been projected for cancer detection in earlier stage. The same attributes for oral and lung cancer which has taken in earlier has been used over here in a further customized way to check the best solution. Earlier for basically image detection methods all the detection methods are used. Here all the detection methods are purely experimental and mathematical analysis based on the clinical value of the attributes[12].

The simple feed forward Neural Network i.e. in fact called a multilayer perceptron. An MLP is a network of perceptron's and castoff for classifying the height. The neurons are positioned in layers with outputs always flowing toward the output layer. If only one layer exists, it is called a perceptron. If multiple layers exist, it is an MLP. A double layer neural network which is capable of calculating 'XOR'. The numerical inside the neurons denotes each neuron's explicit threshold (which can be factored out so that all neurons have the same threshold, usually. This net assumes that if the threshold is not reached, zero (not -1) is output. It is noted that the lower layer of inputs is not considered always, a real neural network layer. This class of networks consists of multi-layer computational units, which is generally interconnected in a feed - forward way. Each neuron in one layer is directed to connect to the neurons of the subsequent layer. In most of the applications the units of these networks apply a sigmoid function in the form of activation function. The theorem of universal approximation for neural network states that every continuous function that maps real number intervals to some output interval of real numbers can be approximated arbitrarily nearby a multi-layer perceptron with a single hidden layer. This result holds only for restricted 'activation functions' classes, for instance, the sigmoid functions. Networks of multi layers use a variety of learning methods, the most prevalent being 'back-propagation'. In this the values of the outputs are compared with the correct answer to compute the value of few predefined error-function. With the help of various techniques the error is then fed back through the network. The algorithm alters the weights of each and every connection using the above information, to reduce the value of the error function by some little amount. Then after repeating the process for an adequately huge number of training cycles the network will generally meet to some state in which the calculation's error is small. In this case one says that the network has learned a definite target function. In order to adjust weights accurately one needs to apply a general method for non-linear optimization task that is known as 'gradient descent'. For this, the error function's derivative with respect to the network weights is computed and the weights are again changed so that the error descends (thus going down on the surface of error function). For this motive, only back-propagation can be applied on networks with distinguishable activation functions. In general the problem of training a network to perform well, even on samples that were not used as samples for training, is a pretty subtle issue that needs extra techniques. This is especially significant for cases in which only very restricted numbers of training samples are obtainable. The threat is that the network unable to fits the training data and unable to seize the true statistical process giving the data. Computational learning theory deals with training classifiers on a very restricted amount of data. In this context of neural networks a simple heuristic, called early 'stopping', usually makes sure that the network will simplify well to examples not in the training set. Other typical disadvantages of the back-propagation algorithm are the convergence's speed and the possibility of finishing up in a local least of the error function. Now there are real-world solutions that can make back - propagation in many layer perceptron's the solution of choice for many machine learning tasks.

IV. Performance Evaluation and Experimental Results

In this section we verified the advantages and properties of our approach by means of lung and oral cancer data set and also we present the performance of Multilayer Perceptron and SLA. The performance of classification algorithms is usually tested by evaluating the accuracy of the concerned classification. Classification accuracy is generally computed determining the percentage of instances placed in the correct class. This rejects the fact that there may be an associated cost involved with a wrong assignment related to the wrong class. We test the performance of classification as is done with information retrieval systems. Only with two sets of classes, the possible outcomes are four in number with the classification. But, the upper left and lower right quadrants are the right actions. The remaining two quadrants are wrong actions:-

Table 5: Properties of Dataset

Dataset	**Instances**	**Attributes**
Lung	**15**	**21**
Oral	**524**	**21**

Table 6: Classification Accuracy

Data Mining Techniques	Classification Accuracy for Lung	Classification Accuracy for Oral
Multilayer Perceptron	**73.3**	**99.82**
Simple Logistic	**60.00**	**99.78**
Radial Basis Function	**59.67**	**93.46**

Table 7: Classification model building time

Data Mining Techniques	Building time for Lung	Building time for Oral
Multilayer Perceptron	**12S**	**10S**
Simple Logistic	**14S**	**12S**
Radial Basis Function	**15S**	**13S**

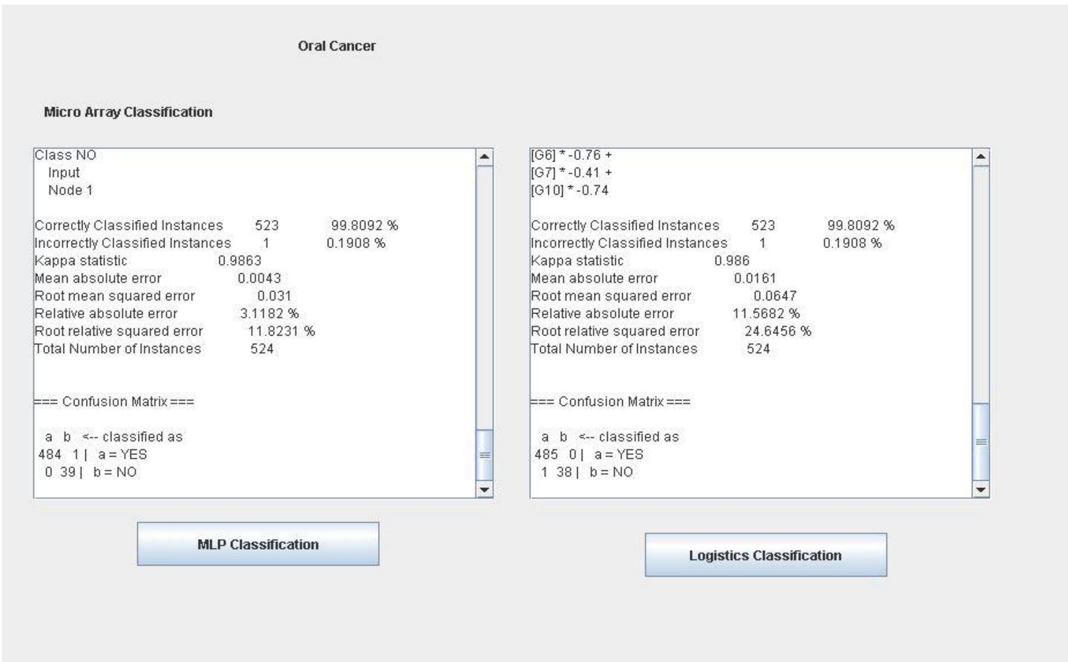

Fig 1: Oral Cancer Classification output

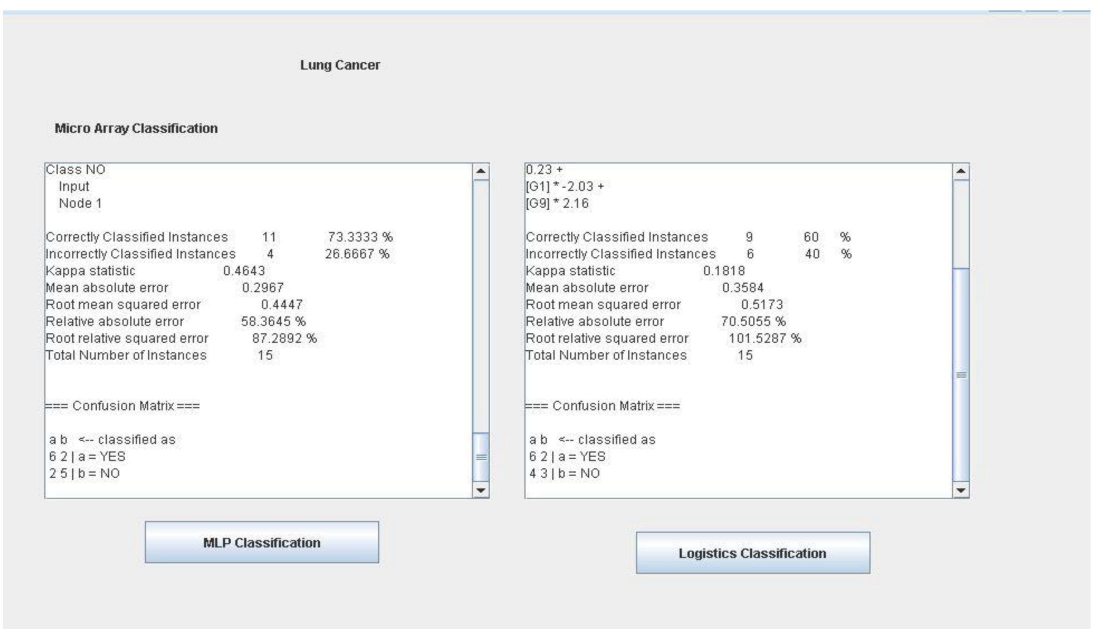

Fig 2:Lung Cancer Classification Output

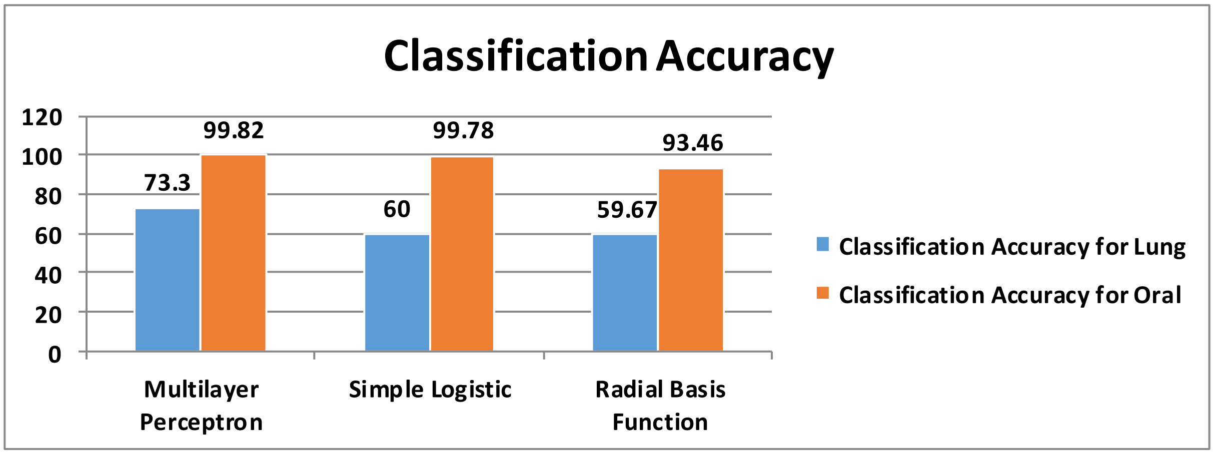

Fig 3: Classification accuracy for Lung Cancer & Oral Cancer Using MLP,SLA,RBF

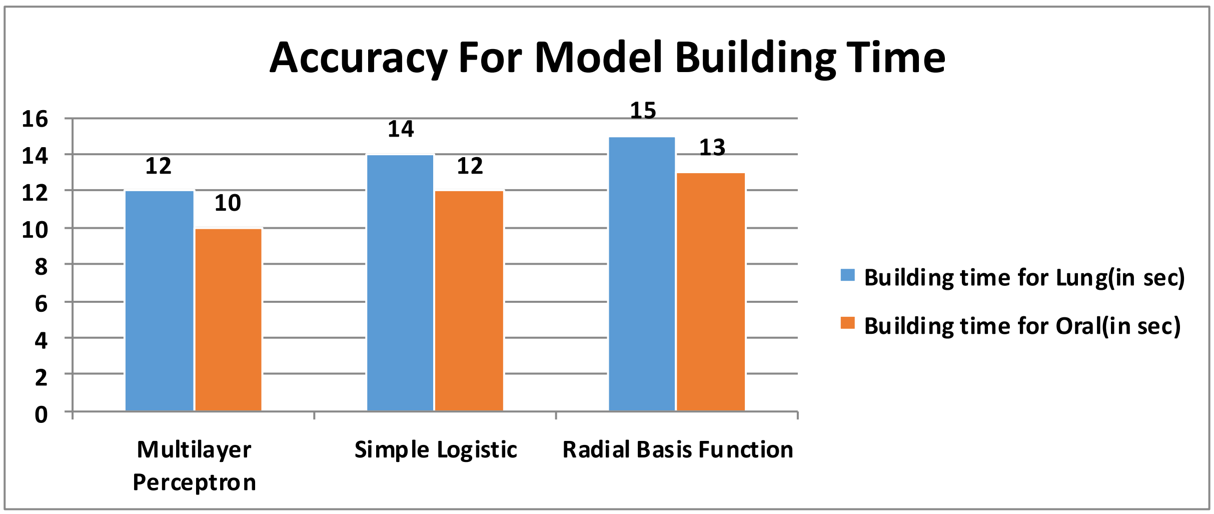

Fig 4: Accuracy measurement for model building time in seconds for Lung Cancer & Oral Cancer Using MLP, SLA, RBF

This segment gives a detailed performance evaluation of MLP, SLA and RBFN. Classification Accuracy is the principal metric for estimating classifier performance and the percentage of test samples that are appropriately and properly classified.

Natural performance measure for classification problems:

• Success: instance's class is predicted correctly
• Error: instance's class is predicted incorrectly
• Error rate: proportion of errors made over the whole set of instances
• Accuracy: proportion of correctly classified instances over the whole set of instances Accuracy = 1 – error rate.

The classification accuracy of 73.3 %, 60 % and 59.67 % for multilayer perceptron, SLA, and the radial basis function, correspondingly for Lung cancer prediction in earlier stage.

V. INVESTIGATIONAL RESULTS

In this section it demonstrated the properties and advantages of our approach by means of lung, oral cancer data set and also present the performance of MLP, SLA & RBFN, correspondingly. The enactment of classification algorithms is typically scrutinized by estimating the correctness of the classification. Classification accuracy is usually intended defining the percentage of occurrences placed in the correct class. This superintends the fact that there also may be a cost related with an incorrect assignment to the wrong class. This perhaps should also be determined. Here the Performance of classification much as is done with attribute selection methods & IRS. With individual two classes, there are four probable consequences with the classification. The upper left and lower right quadrants are correct actions. The remaining two quadrants are incorrect actions.

From the experimental results it is very much clear that by using MLP to classify Lung & Oral cancer it gives the best suitable output than the other two methods SLA and RBFN respectively. Not only in classifying results it is also fastest algorithm for prediction than others as it just taken 12 seconds and 10 seconds to build the model or to make the output in a classified manner to detect lung and oral cancer respectively.

VI. CONCLUSION & FUTURE WORK

Classification is a significant difficulty in data mining. In this work the proposed system settled three different kinds of neural network classifiers: MLP, SLA, RBFN classifier to measure the classification accurateness for Lung and Oral Cancer data set. The decision-making was talented using three Classifiers (MLP, SLA, RBFN), with Lung and Oral cancer data set. The accurateness depends on numerous influences, such as the size and excellence of the training set and also constraints chosen to characterize the input. Having said this, the MLP networks produce more specific, accurate results compared to SLA and RBFN. In future the methods will be used for discovering systems for more large data sets and more complex one by adding immunology of the patient so that the prediction percentage will be more high and reliable.

REFERENCES

[1]N. Friedman, M. Linial, I. Nachman & D. Pe"er (2000), "Using Bayesian Network to Analyze Expression Data", Journal of. Computational Biology, Vol. 7, Pp. 601–620.

J. Han & M. Kamber (2000), "Data Mining; Concepts and Techniques", Morgan Kaufmann Publishers.

[2] D.R. Masys (2001), "Linking Microarray Data to the Literature", Nature Genetics, Vol. 28, Pp. 9–10.

[3] R. Nayak, L.C. Jain & B.K.H. Ting (2001), "Artificial Neural Networks in Biomedical Engineering: A Review", Asia-Pacific Conference on Advance Computation.

[4] H. Midelfart, J. Komorowsk, K. Nørsett, F. Yadetie, A.K. Sandvik & A. Lægreid (2002), "Learning Rough Set Classifiers from Gene Expression and Clinical Data", Fundamental Informatica, Pp. 155–183.

[5] Z. Pawlak (2002), "Rough Set Theory and its Applications", Journal of Telecommunications and Information Technology, Pp. 7-10.

[6] E. Hassanien & J.M.H. Ali (2004), "Rough Set Approach for Generation of Classification Rules of Breast Cancer Data", Informatica, Vol. 15, No. 1, Pp. 23–38.

[7] L.B. Gonçalves, M. M. B. R. Vellasco, M.A.C. Pacheco & F.J. De Souza (2005), "Inverted Hierarchical Neuro - Fuzzy BSP System: A Novel Neuro-Fuzzy Model for Pattern Classification and Rule Extraction in Databases", IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol. 36, No. 2, Pp. 236–248,

[8] I.H. Witten & E. Frank (2005), "Data Mining Practical Machine Learning Tools and Techniques", Second Edition, Morgan Kaufmann Publisher, United States of America.

[9] M. Rocha, Paulo Cortez & José Neves (2007), "Evolution of Neural Networks for Classification and Regression", Neurocomputing, Vol. 70, No. 16–18, Pp. 2809–2816.

[10] Emad W. Saad & Donald C. Wunsch (2007), "Neural Network Explanation using Inversion", Neural Networks, Vol. 20, Pp. 78–93.

[11] Y. Zhao & Y. Zhang (2007), "Comparison of Decision Tree Methods for Finding Active Objects", National Astronomical Observatories, Advances of Space Research, Vol. 41, Pp. 1955–1959.

[12] A. Darwiche (2010), "Review Article on Bayesian Network", Communication of the ACM, Vol. 53, No. 12, Pp. 80–90.

[13] J.M. David & K. Balakrishnan (2010), "Machine Learning Approach for Prediction of Learning Disabilities in School-Age Children", International Journal of Computer Applications, Vol. 9, No. 11, Pp. 7–12.

[14] Mehdi Neshat & Abas E.Zadeh (2010), "Hopfield Neural Network and Fuzzy Hopfield Neural Network for Diagnosis of Liver Disorders", 5 th IEEE International Conference Intelligent Systems (IS), Pp. 162–167.

[15] W.N.H.W. Mohamed, M.N.M. Salleh & A.H. Omar (2012), "A Comparative Study of Reduced Error Pruning Method in Decision Tree Algorithms", IEEE International Conference on Control System, Computing and Engineering, Pp. 392–397.

[16] S. Mandal, G. Saha & RK. Pal (2013), "An Approach Towards Automated Disease Diagnosis & Drug Design using Hybrid Rough-Decision Tree from Microarray Dataset", Journal of Computer Science & Systems Biology, Vol. 6, Pp. 337–343.

[17] S. Mandal & G. Saha (2013), "Rough Set Theory based Automated Disease Diagnosis using Lung Adenocarcinoma as a Test Case", The SIJ Transactions on Computer Science Engineering & its Applications (CSEA), Vol. 1, No. 3, Pp. 75– 82.

[18] S. Mandal, G. Saha & RK. Pal (2013A), "Reconstruction of Dominant Gene Regulatory Network from Microarray Data using Rough Set and Bayesian Approach", Journal of Computer Science & Systems Biology, Vol. 6, Pp. 262–270.

Michie, D., Spiegelhalter, D. J., & Taylor, C. (1994). Machine learning. Neural and statistical classification. Ellis Horwood.

[19]Margaret H.Dunham, "Data Mining - Introductory and Advanced Topics" Pearson Education, 2003, pp. 106-112.

[20] Shital Shah, Adrew kusiak (2007), "Cancer gene search With datamining and genetic algorithms", Computers in Biology and Medicine, Volume 37, issue 2, pp. 251-261, Elsevier.

[21] Linua Li, Hong Tang, Zuobao Wu, Jianli Gong, Michael Gruidl, Jun Zou, Melvyn Tockman, Robert A.Clark, (2004), "Data Mining techniques for Cancer detection using serum proteomic profiling", Artificial Intelligence in Medicine, 32(2), pp 71-83, Elsevier.

[22] Jiawei Han, Micheline Kamber "Data Mining – Concepts and Techniques" Elsevier, 2003, pp 360 to 365.

[23] Bharath, Ramachandran. Neural Network Computing. McGrawHill, Inc., New York, 1994. pp. 4-43.

[24] Margaret H.Dunham, "Data Mining- Introductory and Advanced Topics" Pearson Education, 2003, pp. 112-114

[25] A.Jemal, T.Murray, E.Ward, et al. "Cancer statistics 2005, CA :Cancer J.Clin. 55 (2005). pp. 10-30.

[26] P.Sharma, N.S.Sahni, T.Robert, P.Skaane, U.Petter, B.Hege, J.Marianne, K.Lena, M.Cecilie, S.Pradeep, Z.Alia, A.Jarle, S.Torill, A.A.Lars, S.Ellen, B.Anne-Lise, L.Anders, "Early detection of breast cancer based on gene-expression Patterns in peripheral blood cells, Breast Cancer Res. 7 (2005) R634-R644

[27] M.Gautherine, C.Gross, "Contribution of infrared thermography to early diagnosis, pretheraputic and post-irradiation follow-up of breast carcinomas", Med Mundi. 21(1976) pp. 135-149.

[28] J.R.Harris, M.E.Lippman, U.Vernoesi, W.Willet, "Breast cancer (Part-I), N.Engl.J.Med. 327 (1992) pp. 319-328.

[29]E.Y.K.Ng, Y.Chen, L.N.Ung, "Computerised breast thermography: study of image segmentation and temperature cyclic variations, Int.J.Med.Eng. Technol. 25 (2001) pp. 12-16.

[30]F. Chu, W. Xie, And L. Wang, "Gene Selection And Cancer Classification Using A Fuzzy Neural Network," In Proc. 2004 Annu. Meet. North Amer. Fuzzy Information Processing Soc. (NAFIPS), Vol. 2, Pp. 555–559

[31]S. Mitra, "An Evolutionary Rough Partitive Clustering," Pattern Recognit. Lett., Vol. 25, Pp. 1439–1449, 2004

[32] S. Bicciato,M. Pandin, G. Didon`E, Andc.Dibello, "Pattern Identification And Classification In Gene Expression Data Using An Autoassociative Neural Network Model," Biotechnol. Bioeng., Vol. 81, Pp. 594–606, 2003.

