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Classification of Gastric Carcinoma using Elman Neural network and Autoencoder

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***Abstract*: In medical diagnosis, Breath analysis is one of the non-invasive methods of gaining information of the clinical state of the individual through the exhale breath. Biomarkers play a potential significance in disease diagnosis, thus identification and qualification of the diagnosis is the driving force of the analysis of the exhale breath. Carcinoma a type of cancer that occur on the skin or the tissue lining the organs such as liver, kidney, etc, Gastric Carcinoma occurs in the inner lining of the stomach. The proposed work is to earlier detection of gastric carcinoma at the earlier stage, since it has no significant symptoms. In experimental results Autoencoder produce better results compared with Elman Neural Network in term of statistical accuracy and Mean Square Error.**

Keywords: Autoencoder, Elman Neural Network, Mean Square Error.

1. INTRODUCTION

Breath Analysis is a method of monitoring volatile organic compounds present in the exhaled breath of an individual for gaining non-invasive information on the clinical state of the individual. The area of modern breath testing commenced in 1971, when Noble Prize winner Linus Pauling demonstrated that human breath is a complex gas, containing more than 200 different volatile organic compounds. However, physicians have used Breath Analysis since the days of Hippocrates.

Table 1.1 shows the percentage of composition of human breath. The trace compounds could be endogenous and exogenous. Endogenous compounds are those that are produced inside the human body as a result of metabolism or other physiological processes. Exogenous compounds are those, which are present in the surroundings and absorbed by the body as contaminants.

Table 1. concentration range of various compounds in human breath

Concentration (v/v)	Molecule
Percentage (%)	Oxygen, water, carbon dioxide
Parts-per-million (ppm)	Acetone, carbon monoxide, methane, hydrogen
Parts-per-billion (ppb)	Formaldehyde, acetaldehyde, isoprene, 1-pentane, ethane, ethylene, other hydrocarbons, nitric oxide, carbon disulfide, methanol, carbonyl sulphide, methanethiol, ammonia, methylamine, dimethyl sulphide

2. DATA COLLECTION AND DESCRIPTION

Signal Acquisition System: Six MOS sensors that react to gases with a variation of resistance are used. MOS sensors are characterized by high sensitivity (in the order of ppb), low cost, high speed response and a relatively simple electronics.

The Block diagram of Breath omics is shown in Figure 2. Shows Signal Acquisition system used for Data collection.
The Y axis represents the log (Rs/Ro) where Rs represents the sensor resistance and Ro represents the sensor resistance at 1000ppm. X axis represents the concentration levels in logarithmic terms. From the sensor resistance cerses gass concentration graph, it was observed that there is a linear relation between the voltage output of the sensor module and log of PPM values of gas concentration. X axis represents the Voltage out of

the sensor module and Y axis represents the log of gas concentration. Since there exists a nonlinear relation between the gas concentration level and voltage output of sensor module the prospect of using simple linear devices to linearize the correlation in miserable. Curce fitting is used to derive a statistical correlation between the sensor output voltage and gas concentration level. The relation derived after fitting a curve of sensor is as follows in the equation 1.

$$PPM = \frac{Sensor\ Response}{Circuit\ Voltage} X\ Sensor\ Resistance \tag{1}$$

Circuit Voltage - 5.0 ± 0.2V

Sensor Resistance - Gas Concentration of the Sensor (Table 3.1)

Sensor Response - Output Voltage of the Sensor

Signal Acquisition System

Mouth Piece *Sensor Array* *Acquisition System*

Figure 1. Block Diagram of Breath omics

Assume that there are no other factors that affect the sensor response, then that above equation might be used to determine the gas concentration level between 200ppm – 10000ppm.

Table 2. MOX Sensors sensing layer to detect different target gases

Sensor Type	Number of Units	Target Gases	Gas Concentration (PPM)
TGS 813	2	Methane, Isobutane, Ethanol, Carbon monoxide, Propane, Hydrogen	500 – 10000
TGS 822	2	Methane, Isobutane, Ethanol, Carbon monoxide, Benzene, Acetone	50 – 5000
TGS 2620	2	Methane, Isobutane, Ethanol, Carbon monoxide	50-10000

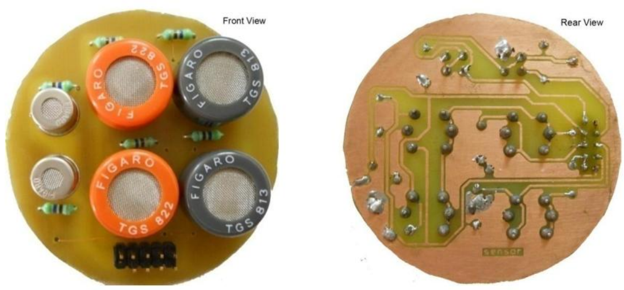

Figure 2. Front and Rear view of the Custom-designed protable metal oxide based chemical sensory module

We employed the breath samples of 161 volunteers were analyzed for this study after excluding: 49 GC patients, 19 patients with benign gastric ulcers and 11 patients with less severe gastric conditions are shown in Table 2.

The less severe stomach conditions included cases with no endoscopic abnormalities (82) and with endoscopic abnormalities without ulceration (11) as in table 3.

Table 3. Table Composition of the Subject Database

Type of Subject	Number	Gender (Male/Female)	Age	Diagnosis
Healthy	82	34/48	20 - 32	Normal
Abnormalities without Ulceration	11	9/2	24 - 35	Endoscopy only
Gastric Ulcer	19	11/8	45 - 58	Endoscopy with Biopsy
Gastric Cancer	49	25/24	38 - 55	

3. CLASSIFICATION

Classification is a supervised learning approach in which the system learns from the data input given to it and then uses this learning to classify new observation. The dataset may be simply be bi-class or it may be multi-class too. Some examples of classification problems are: speech recognition, handwriting recognition, bio metric identification, document classification etc. the types of classification algorithms in Machine Learning: Linear Classifiers, Support Vector Machines, Decision Trees, Boosted Trees, Random Forest, Neural Networks, Nearest Neighbour.

3.1. Artificial Neural Network

Machine Learning methods have been widely used in forecasting a certain problem, especially in medical diagnosis. Medical diagnosis is one of the major problems in medical application. Several research groups working world wide on the development of neural networks in medical diagnosis. Artificial Neural Network (ANN) is a collection of analytical models that find some of the observed properties and used on the analogies of adaptive biological learning. The key elements of ANN model is the unique structure of the information processing system. It is composed of a large number of highly interconnected processing elements that are analogous to synapses.

4. ELMAN NEURAL NETWORK

An Elman network is a three-layer network architecture, similar to a regular neural network with the addition of a set of "context units". The hidden layer is connected to the context units fixed with a weight of one. At each time step, the input is fed-forward and a learning rule is applied. The fixed back-connections save a copy of the previous values of the hidden units in the context units. Thus, the network can maintain a sort of state, allowing it to perform such tasks as sequence-prediction that are beyond the power of a standard multilayer perceptron.

4.1. Experimental Results

Table 4 shows the classification result of Elman Neural network for five different training algorithms. It was observed that the best result obtained by OSS (93.27%), LM (92.84) and RP (92.69) training algorithms

Table 4. Classification accuracy of Elman Neural Network based on Training Algorithms

Training Algorithm	Accuracy %	Sensitivity %	Specificity %	MSE
LM	89.43	91.72	88.59	0.5155
RP	91.47	93.24	90.21	0.1231
OSS	88.12	89.57	86.94	0.7294
GDM	89.33	91.54	87.61	0.5241
GD	90.55	92.83	89.24	0.3496

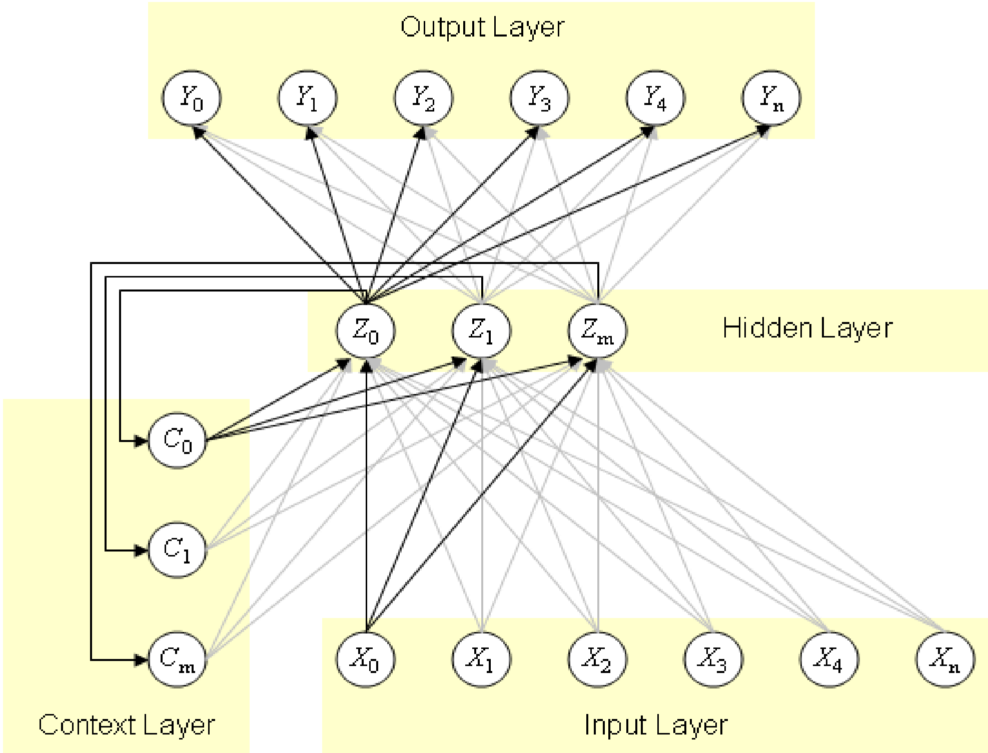

Figure 3. A common structure of an Elman network. Note the context layer, which receives input from, and returns values to, the hidden layer.

5. AUTOENCODER

An autoencoder is one among artificial neural network models used to learn better data coding in an unsupervised manner. The aim is to achieve dimensionality reduction for a set of data which doesn't lose any information using autoencoder through encoding. Recently, this concept has become more widely used for learning generative models of data. Some of the most powerful AI in the 2010s has involved sparse autoencoder stacked inside of deep neural networks.

An autoencoder always consists of two parts, the encoder and the decoder, which can be defined as transitions ϕ and ψ such that:

$$\phi : \mathcal{X} \longrightarrow \mathcal{F} \tag{2}$$

$$\psi : \mathcal{F} \longrightarrow \mathcal{X} \tag{3}$$

$$\phi, \psi = arg_{\phi,\psi} \min || X - (\psi \; o \; \phi)X||^2 \tag{4}$$

In the simplest case, where there is one hidden layer, the encoder stage of an autoencoder takes the input $X \in R^d = \mathcal{X}$ and maps it to $Z \in R^P = \boldsymbol{\mathcal{F}}$:

Autoencoder are also trained to minimize reconstruction error (such as squared errors):

$$\mathcal{L}(x, x') = ||x - x'| \quad |^2 = ||x - \sigma'(W'(\sigma(Wx + b)) + b')||^2) \tag{5}$$

Where x is usually averaged over some input training set.

If the feature space $\boldsymbol{\mathcal{F}}$ has lower dimensionality than then input space $\boldsymbol{\mathcal{X}}$, then the feature vector $\phi(x)$ can be regarded as a compressed representation of the input x. If the hidden layers are larger than the input layer, an autoencoder can potentially learn the identity function and become useless. However, experimental results have shown that autoencoders might still learn useful features in these cases.

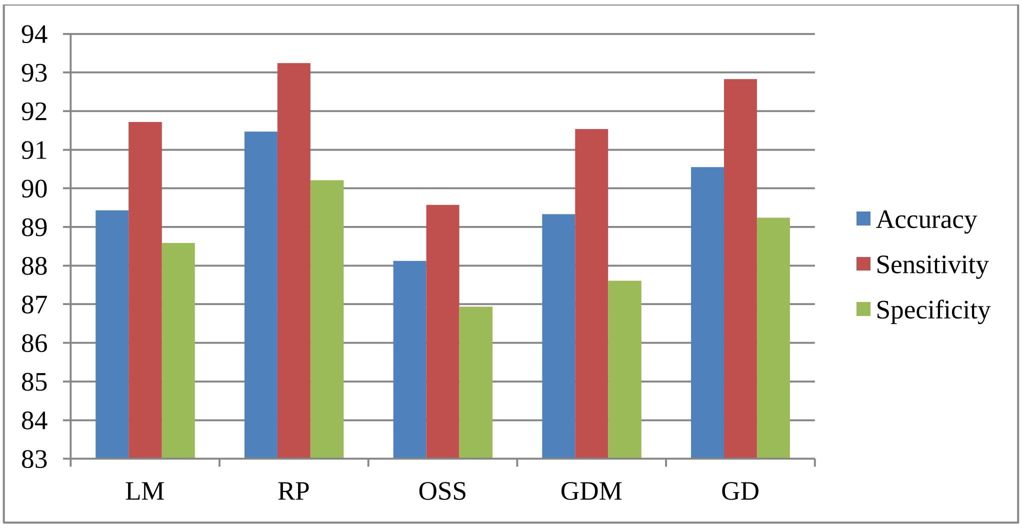

Figure 4. Resilient Back-propagation Training Algorithm outperformance good in Classification accuracy of Elman Neural Network.

The samples are evaluated with 10 hidden layers with two transfer function which are Linear Transfer Function, Saturating Linear Transfer Function is generated as Linear Transfer Function in both the pair (PP), Saturating Linear Transfer Function (SS), Linear Transfer Function followed by Saturating Linear Transfer Function (PS) and Saturating Linear Transfer Function followed by Linear Transfer Function (SP).

Table 5. Comparison of Accuracy, Sensitivity and Specificity with Linear Transfer Function and Saturating Linear Transfer Function.

Transfer Function	Accuracy %	Sensitivity %	Specificity %	MSE
PP	92.56	93.84	91.82	0.1273
SS	92.22	93.27	91.78	0.1352
SP	91.12	92.66	90.88	0.5816
PS	91.69	92.87	91.31	0.4271

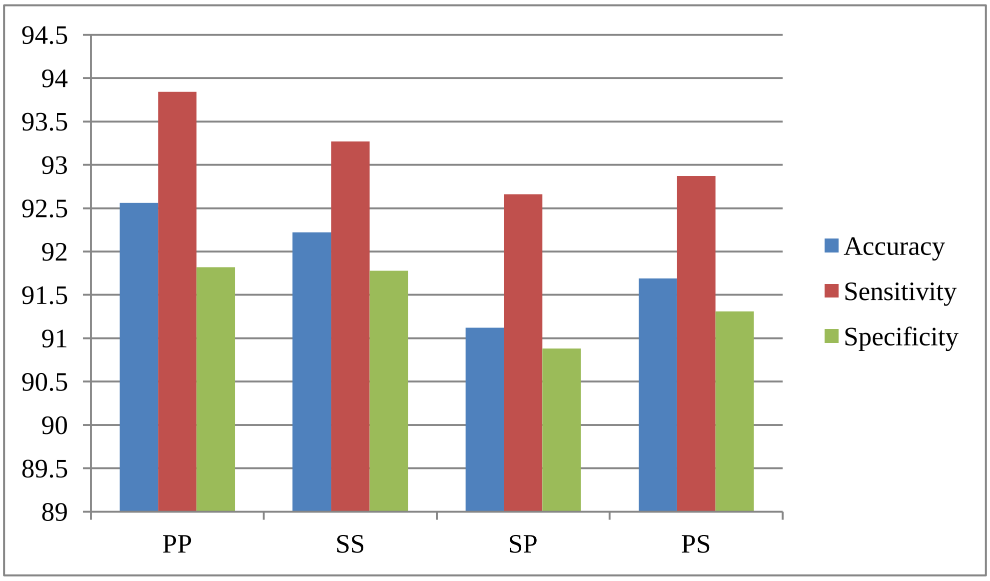

Figure 5. Comparison of Accuracy, Sensitivity and Specificity with Linear Transfer Function and Saturating Linear Transfer Function.

6. CONCLUSION

In this paper variants of Encoder and Decoder Transfer Function have been tested in an Autoencoder to classify the gastric carcinoma as malignant or benign or normal. Based on the obtained result, the Linear Transfer Function produces better result when compared with other Transfer Function and its combination. This is up to the mark of classification accuracy (92.56%) during training of Autoencoder with Linear Transfer Function. It is also observed that in general, Autoencoder provides better classification accuracy opposed to Elman Neural Network to classify the breath samples of Gastric Carcinoma.

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