iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** VIII **Month of publication:** August 2021

DOI: https://doi.org/10.22214/ijraset.2021.37583

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

Effect on Neural Pattern Classifier for Intelligent Gas Sensor by Increasing Number of Hidden Layer

Shikha Srivastava[1], Subhash Kumar Sharma[2]
[1, 2]Asst. Professor, Department of Electronics, MGPG College ,Gorakhpur, India

Abstract: Neural networks are used to solve complex problem viz., speech and image recognition, pattern recognition (Pattern classification), computer vision etc. Pattern classification by using Back Propagation algorithm for an intelligent gas sensor application is presented. The classifier is trained using published data of thick film tin oxide sensor array. Its superior classification and learning performance is demonstrated for discrimination of alcohols and alcoholic beverages by increasing number of hidden layer.
The new model proposed in this article give steep and monotone learning curve and better classification efficiency.
Keywords: Neural Network classifier, Back Propagation Algorithm, system error, classification efficiency, learning curve

I. INTRODUCTION

In an endeavour to achieve human like performance in the field of speech and image recognition (Pattern recognition/classification) scientists and engineers have come up with Artificial Neural Net model or simply ‘Neural Nets’. Modeled after the cerebral cortex of human brain in which ‘natural’ neural network ‘thinks’, ‘feels’, ‘learns’ and remembers. This artificial neural system has emerged fast with powerful and robust capabilities that duplicate the human brain [1-3]. The neural network responds parallel to the inputs presented to it. There is a learning phase during which the weights are adjusted according to certain learning law and working phase during which the weights are frozen and the network is put to operational phase Neural networks are presently applied to solve complex problems viz. speech and image recognition, pattern recognition (Pattern Classification), Computer vision and adaptive control in system like autonomous vehicles. In the recent past substantial efforts have been put in by researchers to improve the performance of intelligent gas sensor (IGS). Reliability and sensitivity of the sensors have been improved to a considerable extent but there poor selectivity limits their capability of gas/odor discrimination. A number of pattern recognition (PR) techniques have been employed to an array of gas sensor data with partially overlapping characteristics the general nonlinear response of individual sensors in an array to varying gas concentrations has led to exploration of different pattern recognition techniques. Partial Model Building [4], Fourier Transform Techniques [5], Cluster Method [6], Transformed cluster Analysis [7], Multiple Regression Method [8], Discriminant Function Analysis [9], etc. have used to analyze sensor array response with different identification capabilities. These PR techniques suffer from two major disadvantages. Firstly, they can be employed only when transduction properties are well behaved e.g. follow a power law. Secondly, they are sequential in nature. In contrast, Artificial Neural Networks (ANN) is capable of handling non linear transduction properties. They are massively parallel in nature and can mimic human response to pattern recognition. Artificial Neural Network (ANN) techniques have been applied for gas/odor discrimination with varying degree of success [10-14]. In all of these attempts, ANN has been trained by using example of sensor array response for crisp classification of gases/ odors. A crisp algorithm generates partitions such that each sensor array response vector is assigned to exactly one class.
Present work aims to increase as well as to see the effect of classification efficiency of neural network by increasing number of hidden layer. To classify, we used supervised Back Propagation algorithm using published data of thick film tin oxide sensor array [15-16], for detecting and identifying the gas/odors present The modification here, provides fast error reductions and better classification efficiency. The utility of the approach proposed here is for modeling for sensor output Values.

II. BASICS OF ANN

Artificial neural network (ANN) is biologically inspired: that is they are composed of elements that perform in a manner that is analogous to the most elementary function of the biological neuron. These elements are then organized in a way that may (or may not) be related to the anatomy of the brain. Despite this ANN exhibit a surprising number of the brain characteristic for e.g. they learn from experience, generalize from previous example to new ones and abstract essential characteristics from inputs containing irrelevant data. Artificial neural networks are not an exact copy of biological human brain, it is important to begin with understanding fundamental concepts of biological neurons and the human brain.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

The human nervous system may be viewed as the three stage system, as shown in block diagram of fig 1[17]. Central to the system is the brain, represented by the neural network, which continually receive information, perceives it and make appropriate decisions. Two set of arrows are shown in fig 1. Those pointing left to right indicates the forward transmission of information-bearing signals through the system. Those pointing right to left signify the presence of feedback in the system. The receptors converts stimuli from the human body or the external environment into electrical impulses that convey information to the neural network (brain). The effectors converts electrical impulses generated by the neural network into discernible responses as system outputs.

An era is going to come when ANN duplicate the function of human brain.

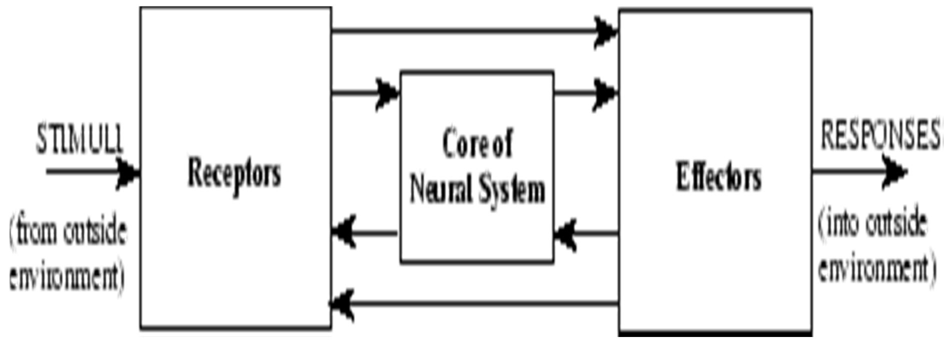


Figure 1: Three Stages of Biological Neural System

Artificial neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts in 1943 (McCulloch & Pitts, 1943). These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks. The basic model of the neuron is founded upon the functionality of a biological neuron. “Neurons are the basic signaling units of the nervous system” and “each neuron is a discrete cell whose several processes arise from its cell body”.

III. HIDDEN LAYER CONCEPT

For nearly all problems, one hidden layer [18] is sufficient. Using two hidden layers rarely improves the model, and it may introduce a greater risk of converging to a local minima. There is no theoretical reason for using more than two hidden layers. DTREG can build models with one or two hidden layers. Three layer models with one hidden layer are recommended.

One of the most important characteristics of a perceptron network is the number of neurons in the hidden layer(s). If an inadequate number of neurons are used, the network will be unable to model complex data, and the resulting fit will be poor.

If too many neurons are used, the training time may become excessively long, and, worse, the network may *over fit* the data. When over fitting occurs, the network will begin to model random noise in the data. The result is that the model fits the training data extremely well, but it generalizes poorly to new, unseen data. Validation must be used to test for this.

IV. WORKING PHASES OF ANN

It works in two phases-

1) During training/learning, a set of training instances is given. Each training instance is typically described by a feature vector (called input vector). It may also be associated with a desired outcome (a concept, a class etc) which is encoded as another vector (called desired output vector). Starting with some arbitrary or random weight setting, the neural network is trained to adapt itself to the characteristic of the training instance by changing weights inside the network. In each training cycle, we present an instance to the network. I generate an output vector, which is compared with the desired output vector (if available). In this way, the error of each output unit is calculated and then used to update relevant weights. In a multilayer network, the errors of hidden units are not observed directly but can be estimated with some heuristic. Each weight change is hopped to reduce error. When all instances are examined, the network will start over with the first instance and repeat. Iterations continue until the system performance (in term of error magnitude) has reduced a satisfactory level
2) During Testing/Sniffing phase, the network propagates information from the input toward the output layer. When propagation stops, the output unit carries the result.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

A free structure of different learning algorithms normally employed for the adoption of synaptic weights is shown bellow in fig.2–

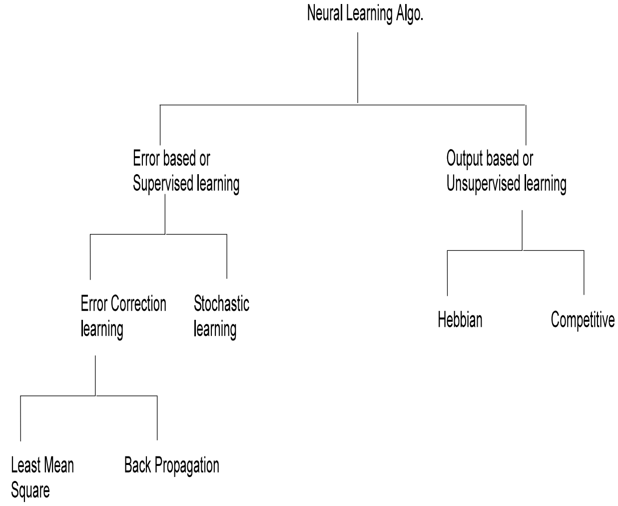


Fig 2

V. PROBLEM FORMULATION

Response of tin oxide sensor array reported by nayak etal. [15], were used in our present work to evaluate the effectiveness of neural network by increasing number of hidden layer, for gas/odor classification. To improve classification efficiency, we have to minimize output error 'e' (e = Y-O) where ,

Y = Target Output

O = Actual Output

First we train the neural network (training phase) using supervised learning (conventional B.P.Algorithm) with 70% data (i.e. 41 samples) [15]. In testing phase a part of data [15] (i.e. remaining 30% data i.e.14 samples, not used in training phase) is used to verify the neural network classifier performance.

VI. REFERENCE NETWORK TAKEN IN OUR WORK (4:6:7 Network)

In this work, three layer (input, hidden, output) having 4, 6, and 7 units (Fig 3) network (4:6:7 topology [16]) is used. In training phase output errors of each sample as well as system error is calculated for 10000 iterations. 41samples [15] have been taken and for each sample there are 7 output errors.

For 1st iteration, 1st sample generates 7 outputs which is propagated back for weight correction and give 7outputs for 2nd sample , which again propagated back for weight correction and give 7 outputs for 3rd sample , which again propagated back and so on…. Up to 41 samples. Same process is repeated for 2nd 3rd... Up to 10000 iteration.

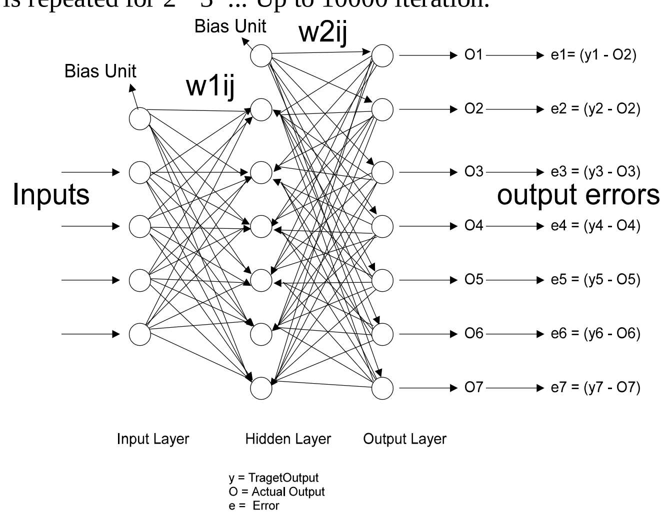


fig 3

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

VII.MODIFICATION

Number of hidden layer in fig 3 is increased as well number of units in each hidden layer is varied and different observations has been taken for classification efficiency with $\alpha = \eta = 0.1$ and $\alpha = \eta = 0.2$. (Appendix). Where α = momentum and η = step size or learning rate both varies in-between 0 to 1.

VIII. SYSTEM ERROR

This Neural Network was trained for 10000 iterations. Values for η, α etc is taken from [16]. The System error was evaluated using the following expressions:

Using Rumelhart`s [19] notation;

$$E_p = \frac{1}{2} \sum_j (y_{pj} - O_{pj})^2$$

System error = $\sum E_p$

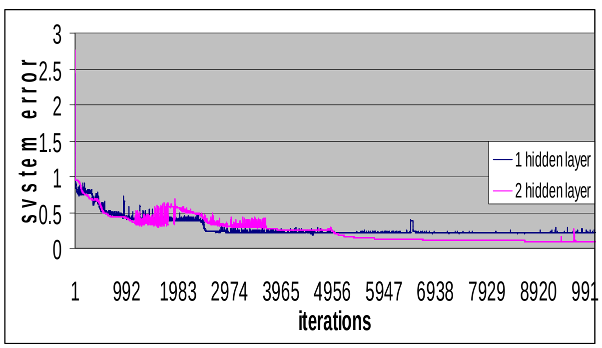
Where Ep is the Sum square error for pth pattern. Ypj the target and Opj the computed output and j is Gas/odor class index, p is the training pattern index

IX. RESULT AND DISCUSSION

System error with one hidden layer for 10,000 iterations is 0.213570 [16], it classifies 9 samples out of 14 samples.

With two hidden layer, we observed three better results for System error for 10,000 iterations in comparison to original [16],which is as follows –

1) With $\eta = \alpha = 0.1$, No. of unit in hidden layer 1=7 and No. of unit in hidden layer 2=4, system error is 0.210829. it classifies 8 samples out of 14 samples. Although the system error is less than original case but classification efficiency does not improve. Hence we can say that reduction of system error may not always improve classification efficiency
2) With $\eta = \alpha = 0.1$, No. of unit in hidden layer 1=8 and No. of unit in hidden layer 2=4, system error is 0.177375. it classifies 11 samples out of 14 samples.
3) With $\eta = \alpha = 0.1$, No. of unit in hidden layer 1=9 and No. of unit in hidden layer 2=6, system error is 0.095502. it classifies 12 samples out of 14 samples. And this is the best result for two hidden layer among all observations taken. Learning curve for system error in this case is shown in graph 1 bellow –



Graph 1

As we can see that we are getting better curve with two hidden layer after approx. 5000 iterations.

With three hidden layer, we did not get any better result for system error in comparison to original result.

X. CONCLUSION

Conclusion of above observation is that increasing further hidden layer may or may not increase the classification efficiency but it certainly increase the complexity of the NN circuit, hence higher number of hidden layers are ruled out. success rate for original case i.e. with one hidden layer is 64.29% and for best case with two hidden layer is 85.71% for discrimination of alcohols and alcoholic beverages and further improvement can be expected by using stronger training algorithm to make it more efficient. The classifier proposed in this article offers implementation advantage as it uses conventional neural network. .

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

XI. APPENDIX

TABLES

OBSEVATIONS

Table 1 : With one hidden layer

No. of units in hidden layer	System error when η= α= .1	System error when η= α= .2	System error when η= α= .3	System error when η= α= .4
1	0.784711	0.938146	0.760147	0.930285
2	0.501898	0.570173	0.760138	0.930285
3	0.446486	0.774991	0.760298	0.757424
4	0.391174	0.403041	0.760315	0.930285
5	0.2622	0.593645	0.760089	0.797657
6	0.2873	0.21357	0.752868	0.930285
7	0.400723	0.346033	0.760182	0.872626

Table 2 : With two hidden layer

No. of units in hidden layer 1	System error when no. of units in hidden layer 2=1 with η=α= .2	System error when no. of units in hidden layer 2=2 with η=α= .2	System error when no. of units in hidden layer 2=3 with η=α= .2	System error when no. of units in hidden layer 2=4 with η=α= .2	System error when no. of units in hidden layer 2=5 with η=α= .2	System error when no. of units in hidden layer 2=6 with η=α= .2	System error when no. of units in hidden layer 2=7 with η=α= .2
1	0.938146	0.763233	0.938145	0.938139	0.93812	0.890741	0.761337
2	0.76079	0.765956	0.938126	0.758742	0.758805	0.938141	0.763197
3	0.726182	0.72413	0.938137	0.758395	0.938136	0.758968	0.762989
4	0.761941	0.586895	0.582353	0.498446	0.587715	0.76007	0.590278
5	0.549674	0.759426	0.369057	0.938596	0.581647	0.760347	0.588616
6	0.5499	0.760235	0.761045	0.643505	0.589541	0.584272	0.428274
7	0.550577	0.938143	0.758316	0.565777	0.580411	0.757714	0.740465
8	0.938144	0.694752	0.581036	0.582237	0.580368		0.348858
9	0.770153	0.586694	0.58433	0.410053			
10	0.549433	0.743917	0.583951	0.5577			
11	0.55066	0.761121	0.740133	0.759574			

Table 3 :With two hidden layer………

No. of units in hidden layer 1	System error when no. of units in hidden layer 2 =1 with η=α= .1	System error when no. of units in hidden layer 2 = 2 with η=α= .1	System error when no. of units in hidden layer 2 =3 with η=α= .1	System error when no. of units in hidden layer 2 =4 with η=α= .1	System error when no. of units in hidden layer 2 =5 with η=α= .1	System error when no. of units in hidden layer 2 =6 with η=α= .1	System error when no. of units in hidden layer 2 =7 with η=α= .1
1	0.939223	0.760002	0.760701	0.93926	0.758386	0.758504	0.916353
2	0.760222	0.772775	0.588094	0.939297	0.746926	0.758126	0.773361
3	0.612585	0.589594	0.759126	0.601309	0.592455	0.416761	0.679411
4	0.939076	0.432803	0.607297	0.570548	0.442886	0.406008	0.498643
5	0.549031	0.791751	0.460389	0.612515	0.298027	0.587027	0.583106
6	0.549955	0.76041	0.588649	0.58384	0.73469	0.407919	0.246931
7	0.596021	0.502245	0.442529	0.210829	0.407541	0.397146	0.41579
8	0.60862	0.676603	0.419731	0.177375	0.394285	0.257113	0.409072
9	0.550201	550201	0.411437	0.250524	0.426458	0.095502	0.560361

Table 4 : With three hidden layer (different cases A - F)

No. of units in hidden layer 1	System error when no. of units in hidden layer 2&3 is 1&1 with η=α= .1	System error when no. of units in hidden layer 2&3 is 2&1 with η=α= .1	System error when no. of units in hidden layer 2&3 is 3&1 with η=α= .1	System error when no. of units in hidden layer 2&3 is 4&1 with η=α= .1
1	0.939224	0.939199	0.939221	0.939214
2	0.751629	0.744758	0.684174	0.734849
3	0.642087	0.625236	0.620573	0.609333
4	0.939192	0.543241	0.538355	0.935811

A

No. of units in hidden layer 1	System error when no. of units in hidden layer 2&3 is 1&2 with η=α= .1	System error when no. of units in hidden layer 2&3 is 2&2 with η=α= .1	System error when no. of units in hidden layer 2&3 is 3&2 with η=α= .1	System error when no. of units in hidden layer 2&3 is 4&2 with η=α= .1
1	0.939218	0.939228	0.939266	0.939250
2	0.760050	0.754546	0.736031	0.736120
3	0.938467	0.745177	0.765975	0.740751
4	0.938184	0.771481	0.766872	0.759045

B

No. of units in hidden layer 1	System error when no. of units in hidden layer 2&3 is 1&3 with η=α= .1	System error when no. of units in hidden layer 2&3 is 2&3 with η=α= .1	System error when no. of units in hidden layer 2&3 is 3&3 with η=α= .1	System error when no. of units in hidden layer 2&3 is 4&3 with η=α= .1
1	0.939261	0.939356	0.939376	0.939256
2	0.760357	0.891376	0.775028	0.760747
3	0.761646	0.893355	0.525128	0.719452
4	0.591096	0.531041	0.739557	0.624931

C

No. of units in hidden layer 1	System error when no. of units in hidden layer 2&3 is 1&4 with η=α= .1	System error when no. of units in hidden layer 2&3 is 2&4 with η=α= .1	System error when no. of units in hidden layer 2&3 is 3&4 with η=α= .1	System error when no. of units in hidden layer 2&3 is 4&4 with η=α= .1
1	0.939307	0.939265	0.939276	0.939254
2	0.761748	0.893260	0.762844	0.761177
3	0.759417	0.920892	0.601190	0.781998
`	0.765204	0.758852	0.564934	0.581178

D

No. of units in hidden layer 1	System error when no. of units in hidden layer 2&3 is 1&1 with η=α= .2	System error when no. of units in hidden layer 2&3 is 2&1 with η=α= .2	System error when no. of units in hidden layer 2&3 is 3&1 with η=α= .2	System error when no. of units in hidden layer 2&3 is 4&1 with η=α= .2	System error when no. of units in hidden layer 2&3 is 1&2 with η=α= .2	System error when no. of units in hidden layer 2&3 is 2&2 with η=α= .2	System error when no. of units in hidden layer2&3 is 3&2 with η=α= .2	System error when no. of units in hidden layer 2&3 is 4&2 with η=α= .2
1	0.938147	0.938145	0.938148	0.938147	0.938145	0.938146	0.938140	0.938157
2	0.938143	0.760023	0.729158	0.761023	0.759020	0.763294	0.938088	0.817460
3	0.665741	0.761028	0.760981	0.667161	0.797639	0.619301	0.938137	0.758713
4	0.938143	0.938144	0.549854	0.761023	0.934269	0.542940	0.938144	0.581644

E

No. of units in hidden layer 1	System error when no. of units in hidden layer 2&3 is 1&3 with η=α= .2	System error when no. of units in hidden layer 2&3 is 2&3 with η=α= .2	System error when no. of units in hidden layer 2&3 is 3&3 with η=α= .2	System error when no. of units in hidden layer 2&3 is 4&3 with η=α= .2	System error when no. of units in hidden layer 2&3 is 1&4 with η=α= .2	System error when no. of units in hidden layer 2&3 is 2&4 with η=α= .2	System error when no. of units in hidden layer2&3 is 3&4 with η=α= .2	System error when no. of units in hidden layer 2&3 is 4&4 with η=α= .2
1	0.938147	0.938148	0.938162	0.938417	0.938151	0.938152	0.938148	0.938146
2	0.938144	0.764507	0.938142	0.758550	0.938141	0.668088	0.938142	0.593723
3	0.933999	0.938136	0.934665	0.918082	0.938142	0.792795	0.938138	0.725232
4	0.938141	0.706398	0.938144	0.763125	0.760691	0.737738	0.938142	0.738881

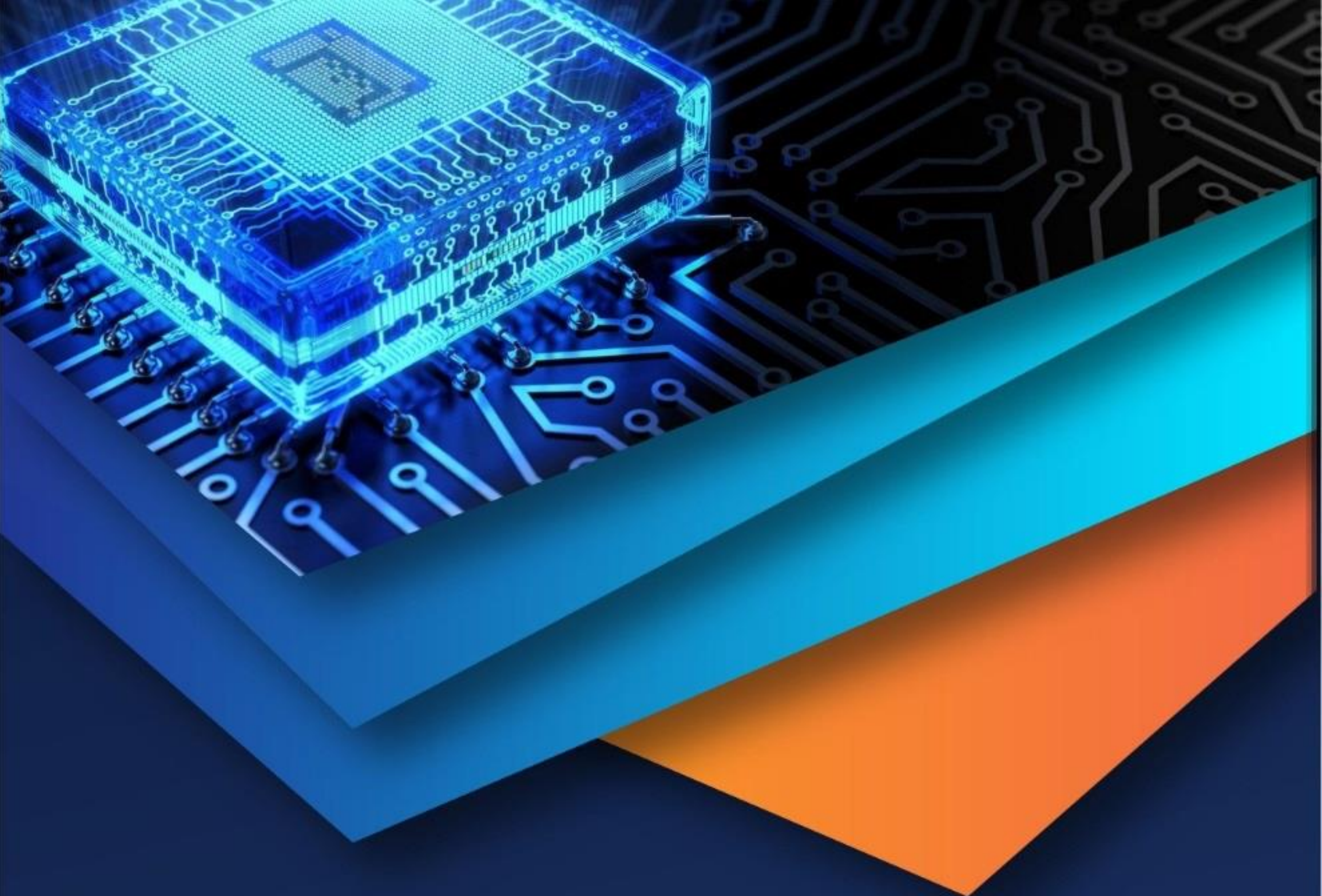
F

REFERENCES

[1] V.Vermuri, Ed,Computer Society Press Technology Series : Neural Networks, The Computer Society Press of the IEEE,1998.
[2] MaureenCaudill,Neural Networks Primer, Parts 1 to V, AI Expert, Dec.1987, Feb. 1988, Jun 1988, Aug. 1988, Nov. 1988.
[3] Special issue on Artificial Neural Systems, IEEE Computer, Vol. 21, March 1988.
[4] G.Horner. C.Hierod.Gas analysis by partial model building, Sensors and Actuators B 2 (1990) 173-174.
[5] W.M.Sears,K.Colbow,Selective thermally cycled gas sensing using fast fourier transform techniques, Sensors and Actuators_B 2 (1990) 283-289.
[6] H.V.Shurmer, J.W.Gardner,H.T.Chan, The application of discrimination techniques to alcohols and tobaccos using tin oxide sensors and actuators B 18 (1989) 361-371.
[7] M.S. Nayak, R.Dwivedi and S.K. Srivastava: Transformation of cluster analysis: ans approach to identification of gases/odors. Using an integrated gas sensor array, Sensors and Actuators_B 12 (1993) 103-110.
[8] J.C.Legras, et al.: Application of multiple regression method and automatic testing equipment to the characterization of smart sensors. Sensors and Actuators B 12 (1987) 235-243
[9] J.W. Gardner,H.V. Shurmer, T.T. Tan: Application of electronic nose to the discrimination of coffees, Sensors and Actuators_B (1992) 71-75
[10] J.W. Gardner, E.L.Hines, H.C. Tang: Detection of vapors and odors from a multi-sensor array using pattern recognition techniques. Part II: Artificial Neural Network, Sensors and Actuators_B 9(1992) 9-15.
[11] T. Nakamoto,A.Fakuda, T.Moriizumi: Perfume and flavor identification by odor sensing system using quartz resonator sensor array and neural network pattern recognition, sensors and Actuators_B 10 (1993)85-90.
[12] P.S. Barker, J.R.Chen, N.E.Agbor, A.B.Monkman, P.Mars, and M.C.Pelty: Vapour recognition using Organic film and Artifitial neural networks, Sensors and Actuators_B 17 (1994) 143-147.
[13] H.Debeda, D.Rebiere, J.Pistre, F.Menil: Thick film pellistor array with a neural network post treatment, Sensors and Actuators_B 26 (1995) 297-300.
[14] M.Sehweizer-Berberich.J.Goppert, A Hierlemann, J.Mitrovies. U. Weimer. W. Rosentiel, W. Gopel: Application of neural network Systems to dynamic response of polymer- based sensor arrays, Sensors and Actuators_B 26-27 (1995) 232-236

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VIII Aug 2021- Available at www.ijraset.com

[15] M.S Nayak, R.Dwivedi, S.K. Srivastava: Integrated sensor array for detection of alcohols and alcoholic beverages, journal of Institution of Engineers (INDA) - ET 75 (1995) 94-98.
[16] R.R.Das, K.K.Shukla, R.Dwivedi, A.R. Srivastava: Discrimination of individual gas/odor using responses of integrated thick film tin oxide sensor array and fuzzy-neuro concept, Microelectronics journal 30 (1999) 793-800.
[17] Simon Haykin, A Handbook on Neural Networks, A comprehensive foundation, second edition
[18] Multilayer Perceptron Neural Networks.htm, www.dtreg.com/
[19] D.E Rumelhartand, J.L.McClelland (Eds.): Parallel Distributed Processing, I, MIT Press, Cambridge, MA, 1986, pp.318-362.



10.22214/IJRASET

INDEX COPERNICUS 45.98

ISRA JIF IMPACT FACTOR: 7.129

SJIFactor TOGETHER WE REACH THE GOAL IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY