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AN INTELLIGENT SYSTEM FOR FISH FRESHNESS QUALITY ASSESSMENT USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In this work we demonstrate the design methodology for An Intelligent Fish freshness system for real time classification of the freshness of fish using Artificial Neural Network (ANN). Automated Fish freshness assessment and identification plays an important role in fisheries industry applications. This method is based on the series of sensor connected together with Arduino to improve the performance of fish freshness quality assessment. The result is used for the fish freshness using artificial neural network (ANN). The series of sensor node design involves three major parts (1) the gas sensing elements i.e. (sensors) (ii) A Single board microcontroller unit (Arduino) (iii) Artificial Neural Network (ANN). The Sensor interfacing methodology has been demonstrated in practice, by considering MQ series (MQ-4,MQ-2,MQ-8,MQ-7,MQ-5 and MQ-135) of Gas sensors elements, With the single board microcontroller i.e. Arduino Uno, in our case. Once the series of gas sensors has been interfaced with the single board microcontroller, the signals from the physical gas sensors are captured by running a software PLX-DAQ. Data was collected from 3 different selected species. (i) Tilapia Fish (ii) Carpio Fish and (iii) Tengra Fish over a period of several days. The ANN was trained with many samples as collected while testing was done only by using fresh fish data (Day 1), Semi-spoiled Fish (Day 2) and spoiled fish data (Day 3) by using 9 samples of three different species. The entire test samples were classified with 99% accuracy. The classified output has a mean square error of 1.4155×10^{-17} at 9022 epochs for Tilapia, mse of 5.9805×10^{-13} at 9448 epochs for Carpio and mse of 5.925×10^{-18} at 10,000 epochs for Tengra. Intelligent processing of the sensor patterns involves the use of a dedicated ANN for each species under study. The ANN has been trained

in NCC laboratory IIT (BHU), Varanasi conditions with ensuring reliability, accuracy and repeatability. The proposed system has been successful in identifying the number of days after catching the fish with an accuracy of up to 99%.

List of Figures

List of Tables

List of Abbreviations

ANN	Artificial Neural Network
USB	Universal Serial Bus
TMAO	Trimethylamine Oxidase
DMA	Dimethylamine
IUCN	International Union for Conservation of Nature
VOC	Volatile Organic Compound
FEM	Finite Element Model
BM	Britter Mcquaid Model
PLX	Parallax
CNG	Compressed Natural Gas
ADC	Analog to digital Converter
LPG	Liquefied Petroleum Gas
IDE	Integrated Development Environment
MSE	Mean Square Error
PCA	Principal Component Analysis
SPCA	Standardized Principal Component Analysis
AI	Artificial Intelligence
CNN	Convolution Neural Network

Table of Contents

CHAPTER 1

1. INTRODUCTION

1.1 INTRODUCTION

Fish is the most perishable of flesh foods, but is held in high regards for its flavor and health benefits [1]. On a pound for pound basis, seafood is as safe, if not safer, than other meat sources [2].The safest seafood supply in the world is found in the US because the government, in conjunction with the food processing industry, has taken steps to ensure safety [2]. The largest difficulty in maintaining safe and fresh seafood, according to the FDA, is that half of the seafood consumed in the US is imported from more than 35 countries and therefore, does not undergo the same scrutiny as domestically produced fish, until it reaches the US [3].

Moist fresh fish will have almost no fishy odor. The fishy odor will develop with time after harvest, but should never be strong or objectionable. A strong ammonia smell is probably the result of protein breakdown and usually indicates old product, extended freezer storage, or possibly, mishandled product by storage at elevated temperature above 4 °C (temperature abused) [4]. In some species, the enzyme trimethylamine oxidize (TMAO) is responsible for protein changes and excessive moistures loss during thawing, producing a dry and cores textured product that smells of ammonia [4].

Fish degradation after death is generally attributed to bacterial decay, enzymatic degradation, and lipid oxidation. Bacteria reside on the surface, gills, and in the gut of living fish, are the major cause of seafood spoilage. After harvest, the bacteria invade the flesh through the gills, skin, stomach lining and blood vessels [5]. Enzymes, Such as TMAO are present in some species, causing the flesh to soften, lowering quality and producing more food for bacteria, accelerating spoilage rate. Oxygen in the air attacks oils and causes rancidity, off-odors and flavors [5].

1

Decomposition does not always occur evenly within a single fish or between fish in a catch. Generally decomposition begins in the interior end of a fish and in the belly flaps, but exceptions have been observed. The rate and type of spoilage can vary with the time of year, species being harvested and method of harvest [5]. When loss of quality occurs and spoilage begins, the process cannot be reversed and the product quality is lost.

There are no universally recognized methods for determining the freshness of fish. There are many mechanisms for fish degradation and the current best method of measuring the quality is by human sensory panels. A number of groups are attempting to come together and define the problems and outline a systematic approach to creating an acceptable and accurate method for fish freshness monitoring [6].

Many groups are attempting to develop an ―electronic nose‖ for fish freshness measurements and most of them are developing sensors for specific gases that are assumed to be fish degradation products, such as trimethylamine (TMA) and dimethylamine (DMA) [7-10].

Fish species identification and automated fish freshness assessment play important roles in fishery industry applications. Automatic fish sorting by species is an important process for many fishery applications such as freshness assessment, marine ecology issues, and automate logging of the catch in commercial and research fishing vessels. In this work, fish identification is done with the aim of improving the accuracy of freshness assessment system. Traditionally, the patterns of fish skin as well as the whole shape have been used by fishery researchers to identify the fish. However, the lighting conditions, freshness of the fish, and changes in skin colour influence the fish type identification. This makes it difficult to manually classify the fish species and correctly interpret the findings.

2

An Intelligent System for Fish Freshness Quality Assessment Using ANN

The use of fish image as inputs for the training system was not effective as neither memory usage is neither optimum nor fish type and its freshness is easily recognizable. Fish freshness identification based on fish body degradation and useful data set extracted from these fishes is the methodology adopted in the designed system.

A successful sensor array system for fish freshness is trained with fresh [Day1], Semi Spoiled [Day 2] and Fully Spoiled fish [Day 3]. The local Varanasi Market (Ramnagar Fort Fish Market) Fish were selected for testing in this work. These are Fish A (Tilapia), Fish B (Carpio), Fish C (Tengra).

1.1 Tilapia

Tilapia is the common name for nearly a hundred species of cichlid fish from the tilapiine cichlid tribe. Tilapia are mainly freshwater fish inhabiting shallow streams, ponds, rivers and lakes and less commonly found living in brackish water.

–Not all fish have the same fatty acid profile. But this fish (Tilapia) in moderation is fine. It has lower Cholesterol than red meat and it is easy to cook it. So eating Tilapia is not the same as eating bacon‖

This fish have been of major importance in artisanal fishing in Africa and they are of increasing importance in aquaculture and aquaponics. Tilapia can become a problematic invasive species in new warm-water habitats such as Australia whether deliberately or accidentally introduced, but generally not in temperate climates due to their inability to survive in cold water. Tilapia is the fourth most consumed fish in the United States dating back to 2002. Tilapia is popular because of its low price, easy preparation, and its mild taste. It is one of the three main types of fish caught in Biblical times from the Sea of Galilee specifically the "Galilean Comb".

3

1.1.1 Characteristics

Tilapia typically has laterally compressed, deep bodies. Like other cichlids, their lower pharyngeal bones are fused into a single tooth-bearing structure. A complex set of muscles allows the upper and lower pharyngeal bones to be used as a second set of jaws for processing food (cf. morays) allowing a division of labor between the "true jaws" (mandibles)and the "pharyngeal jaws". This means they are efficient feeders that can capture and process a wide variety of food items. Their mouths are protractible, usually bordered with wide and often swollen lips. The jaws have conical teeth. Typically tilapia have a long dorsal fin, and a lateral line which often breaks towards the end of the dorsal fin, and starts again two or three rows of scales below. Some Nile tilapia can grow as long as two feet.

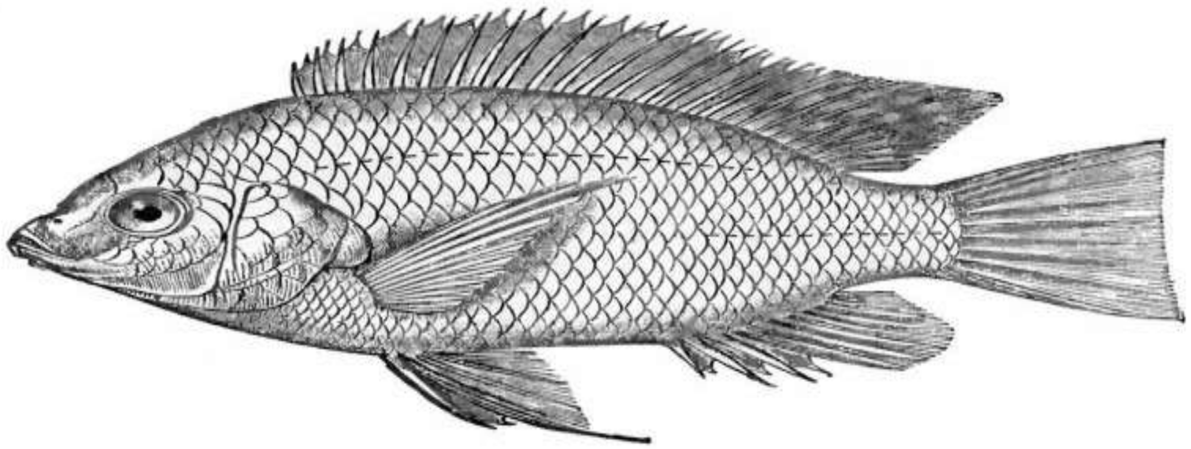


Figure 1.1 Fish-(A)- Tilapia

4

Figure 1.2 Fish A (Tilapia) Taken for collecting data set

Other than their temperature sensitivity, Tilapia exists in or can adapt to a very wide range of conditions. An extreme example is the Salton Sea where tilapia introduced when the water was merely brackish now lives in salt concentrations so high that other marine fish cannot survive. Tilapia is also known to be a mouth breeding species. Mouth breeding means they carry the fertilized eggs and young fish in their mouths for several days after the yolk sac is absorbed. Tilapia rarely competes with other "pond" fish for food. Instead, because they consume plants and nutrients unused by other fish species and substantially reduce oxygen-depleting detritus; adding tilapia often increases the population, size and health of other fish. They are used for zoo ponds as a source of food for birds. Tilapia can be farmed together with shrimp in a symbiotic manner positively enhancing the productive output of both.

1. CARPIO Fish

The common Carp or European carp (Cyprinus Carpio) is a widespread freshwater fish of eutrophic waters in lakes and large rivers in Europe and Asia. The native wild populations are considered vulnerable to extinction by the International Union

5

for Conservation of Nature (IUCN), but the species has also been domesticated and introduced (see aquaculture) into environments worldwide, and is often considered a destructive invasive species being included in the list of the world's 100 worst invasive species. It gives its name to the carp family Cyprinidae.

Figure 1.3 Fish B - (Carpio)

Wild common carp are typically slimmer than domesticated forms; with body length about four times body height, red flesh, and a forward-protruding mouth. Common carp can grow to very large sizes if given adequate space and nutrients. Their average growth rate by weight is about half the growth rate of domesticated carp. They do not reach the lengths and weights of domesticated carp, which (range, 3.2-4.8 times) can grow to a maximum length of 120 centimeters (47 inch), a maximum weight of over 40 kilograms and an oldest recorded age of 38 years. The largest recorded carp, caught by an angler in January 2010 at Lac de curtons (Rainbow Lake) near Bordeaux, France, weighed 42.6 kilograms. The largest recorded carp, caught by British angler, Colin Smith, in 2013 at Etang La Saussaie Fishery, France, weighed 45.59 kilograms . The average size of the common carp is around 40-80 cm (15.75-31.5 inches) and 2-14 kg.

6

Figure 1.4 Fish B (Carpio) taken for collecting data set

Reproduction - An egg-layer, a typical adult female can lay 300,000 eggs in a single spawn. Although carp typically spawn in the spring, in response to rising water temperatures and rainfall, carp can spawn multiple times in a season. In commercial operations, spawning is often stimulated using a process called hypophysation, where lyophilized pituitary extract is injected into the fish. The pituitary extract contains gonad tropic hormones which stimulate gonad maturation and sex steroid production, ultimately promoting reproduction.

7

Figure 1.5 Fish C -Tengra Fish

Tengra - Tengra is the members of any of the five species of Mystus, small-sized catfishes of the family Bagridae, orderSiluriformes. Body scaleless; barbels surround the mouth. This fish contains significant amount of protein, fat, calcium and iron. According to a report by the Directorate of Fisheries Tengra fish contains 1.5 times higher calorific value than Rui fish (labeorohita).

Figure 1.6 Fish C- (Tengra) taken for collecting data

The five species of Tengra occurring in Bangladesh can be recognized by the following features: (i) Golsha Tengra (Mystusbleekeri) – Its body is brownish and lighter in weight. There are 2 light longitudinal bands, one above and the other below the lateral line. It attains a body length up to 14 cm as shown in figure 1.5.

8

(ii) Tengra (M. vitiates) - It has two dark wide bands above and two narrow bands below lateral line and It attains a length of about 10 cm.

(iii) Gulitengra (M. gulio) - Its body is brown on back, dull white below. Mandibular barbells partly black. It attains a length of about 20 cm.

(iv) Kabasi Tengra (M. cavasius) – It have black spot present at the base of the dorsal spine and It attains a length of about 15 cm.

(v) Bujuri Tengra (M. Tengra) – Its body is also brownish, a black spot behind operculum. Few longitudinal bands are present on the body. Attains a length of about 6 cm. maximum lengths reported 7 cm (Bhuiyan, 1964) and 6.2 cm (Rahman, 19889). This species usually found in weedy, sandy and muddy places of the pools, streams and river in the rainy season.

1.2 Gas Sensor

There are many fields in which Gas sensors are broadly used, for example in environmental monitoring of automobile industry outputs, the prevention of natural disasters, and other pollution-related industries.[1-4] In a modern world, there is a great need of small, flexible, and inexpensive gas monitors. For example, Gas detection plays an important, even essential role in many areas, ranging from food safety to environmental monitoring; with one of the best known examples being fire alarms based on CO detection [5],[6]. Another possible application of such an intelligent gas sensor system is Environmental protection. The spreading of gaseous emissions from a chemical accident or fire can be measured and followed with a mobile or stationary network of gas sensor systems. So people easily can be warned if there are unhealthy

9

compounds and concentration in air. It has been the goal to develop and investigate such an intelligent gas sensor system for identification and quantification of hazardous compound. Therefore, The design of inexpensive, reliable, fast responding, highly sensitive, and low-power consuming array chemosensory systems also referred to as electronic nose systems (e-nose) has long been recognized a primary goal for the chemo sensing community. To detect Combustible, flammable, toxic gases and oxygen depletion, Gas sensors can be used. Gas detectors are usually battery operated. When dangerous levels of gas vapors are detected, they transmit warnings via a series of audible and visible signals such as alarms and flashing lights, but there are also new systems for remote monitoring. An essential element of the semiconductor plant‘s safety system is reliable gas detection and monitoring systems. A variety of systems are available for different monitoring applications. There are many types of gas sensors, which are used for gas detection. Sensors which are currently available in market detect only single gas and are costly.Therefore, intelligent and inexpensive personal monitors are needed, which can identify and quantify more than one species of gas. In past the models used for gas leakage are Gaussian plume [7] and puff model [8], 3-D finite element (FEM-3) model, Britter and McQuaid (BM) model, Sutton model and gas turbulent diffusion model [9].

Specifically, to detect specific gases based on the variation in resistance or thermal conductivity due to absorption or desorption on the surface of an oxide semiconductor, a semiconductor gas sensor is used. Using the correct system will result in managing gas

10

hazards in the most effective and efficient way. Semiconductor gas sensors (metal oxide sensors) are electrical conductivity sensors. The resistance of their active sensing layer changes due to contact with the gas to be detected. In the ideal case, the gas reacts with the sensor surface in a completely reversible reaction. Due to their chemical composition and properties, metal oxide gas sensors are well-suited for a wide range of applications and for the detection of all reactive gases. Depending on the material used and the gases that need to be detected, typical operating temperatures range between 300°C and 900°C. Semiconductor gas sensors can be used for a wide array of applications, ranging from safety equipment (explosion, leakage, contamination and poisoning protection)up to emissions and air quality monitoring, quality assurance, process instrumentation and measurement technology. The measuring range depends on the gas being detected and covers from a few ppm into the percentage. The detection limit depends on the respective gas sensitive material. Based on the design of the sensor, the power consumption of the metal oxide gas sensors varies.

These gas sensors are rapid and have simple structures with low manufacturing costs. But, in terms of accuracy and selectivity they have few shortcomings. Thus, the most important requirements are to achieve stability and reliability while keeping the above mentioned merits. To fulfill these requirements there is need to improvements in stability, high resolution, repeatability, and economic feasibility. In several applications micro and nanotechnology based gas sensors have allowed for the detection of an important set of gases. For optimal gas sensor performance, several issues such as sensitivity, selectivity, stability, and time of response should be simultaneously addressed. To achieve selectivity with high sensitivity and maintain high sensitivity under high humidity conditions are critical issues for the realization of an effective gas sensor. Selectivity allows a gas sensor to detect the presence of particular gases

11

in media, including other gases, and can be very hard to achieve under normal atmospheric conditions [10-16].

Sensitivity:

Sensitivity is the measure of the change in output of a sensor for a change in the input. It is the minimum value of target gases‘ volume concentration when they could be detected[17].

Selectivity:

Selectivity can be called at the ability of gas sensors to identify a specific gas among a gas mixture.[17]. Gas sensors usually have the drawback of poor selectivity, causing them to respond, not necessarily uniquely to multiple analytes, which is also known as cross-sensitivity. The responses from a cross-sensitive sensor are therefore intrinsically ambiguous and can‘t serve as unique identifiers or signatures for gas samples of completely unknown composition. There are two approaches to improve selectivity. The aim of first method is to prepare a material that is specifically sensitive to one compound and has almost zero cross-sensitivity to other compounds that may be present in the working atmosphere. Specific sensitivity to one compound is regularly achieved either by modulation of the sensor temperature or through the use of sensor arrays due to difficulties in distinguishing the specific sensitivity to one compound when only one sensor signal is employed. To increase the selectivity or accuracy of gas sensors, instead of increasing the dimensions of gas signatures, the exploitation of sensor arrays has some extended functions such as damping cross-sensitivity at special situations and eliminating environmental impacts. For instance multiple sensors could be tuned to detect a specific gas in a mixture by heating it to the temperature of maximum sensitivity for that gas and thus avoid the cross-sensitivity at some temperature point.

12

The fundamental requirements for sensors in a sensor array are given below:

(1) Sensors should be functionally stable and reliable.

(2) Sensors respond to different kinds of gases, *i.e.*, sensors possess the cross-sensitivity to some extent. This could help reduce the amount of sensors and increase the array efficiency.

(3) The response and recovery time should be short, which reflects the detection efficiency of sensors. Otherwise, sensors will suffer from errors for being unable to follow the changes of gas composition and concentration in the gas chamber.

The second approach is based on the preparation of materials that can discriminate among several analytes in a mixture. Such discrimination is possible because of the different adsorption and reactivity properties of the analytes to the materials. Many studies have been focused on the development of optical sensor systems; these types of devices offer interesting advantages compared to electronic ones such as their light weight, remote measuring capability, and electromagnetic immunity. Therefore, no electric signal is necessary, which can eliminate any kinds of risks from explosion in the detection of specific volatile organic compounds (VOCs). [18-24]

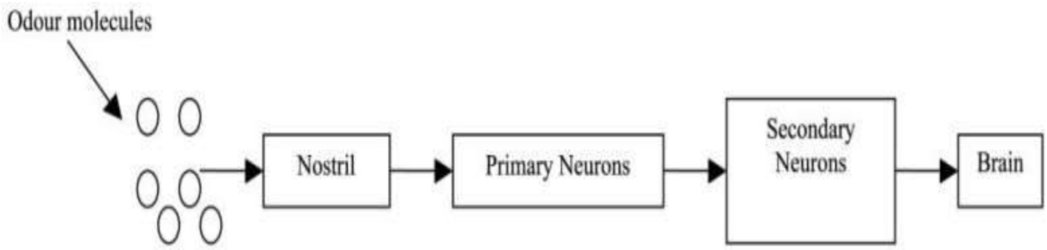
1.3 Pattern Recognition Technique

To describe the methodology of solving classification problems the term pattern recognition is used. Given an object, assigning it to one of predefined target categories or classes is called classification. Classification is the process of finding a set of models or functions that describe and distinguish data classes or concepts, for the purpose of predicting the class of objects whose class label is unknown. Classification is important for management of decision making. The goal of classification is to accurately predict the target class for each case in the data.

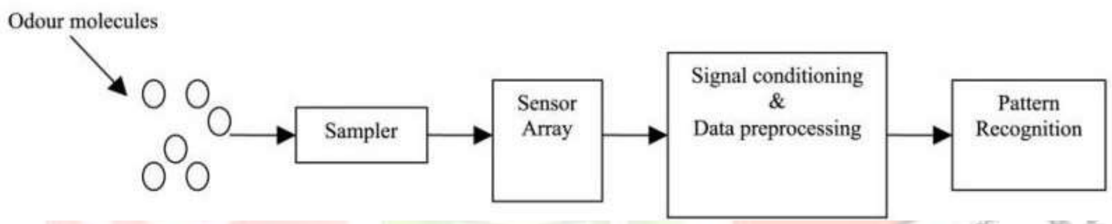
13

1.4 Statistical Methods for Artificial Olfaction

The statistical and pattern recognition techniques are applied to gas sensor arrays (also called Electronic Noses – EN).



(a)



(b)

Figure 1.7 Comparison of the (a) e-nose system and (b) mammalian olfactory system

For exploratory data analysis in the gas sensor field, Principal Component Analysis (PCA) is still the mostly used technique, although the human judgment of PCA plots often determines the classification results. It is a procedure for identifying a smaller number of uncorrelated variables, called "principal components", from a large set of data. Clustering is particularly appropriate for exploratory data analysis. Cluster analysis (CA) is the unsupervised classification of patterns (feature vectors) into groups (clusters) so that individuals within the same group are more similar to each other than those belonging to different groups. This methodology of classification enables us to summarize information, e.g. by representing classes through prototypes, and can help

14

detecting important relationships and structures within the data sets. Cluster validity (CLV) techniques can be used to objectively and quantitatively assess the structure of experimental data. For Cluster Analysis and Cluster Validity, a Mat lab-based platform is developed by sensor, which implements different types of clustering algorithms (hierarchical agglomerative clustering, k-means and fuzzy c-means) and a number of state-of-the-art internal and external validity indices. Statistical methods are parametric as they assume that the data may be described in terms of probability density functions. These include Principal component regression (PCA),partial least squares (PLS), discriminant factor analysis (DFA), Principle Component Analysis (PCA), hierarchical cluster analysis (HCA), analysis of variance between groups (ANOVA), regression method, principal components regression (PCR), soft independent modeling class analogy (SIMCA) and clustering algorithms such as k-means[25], [26].

1.5 Non statistical methods:

In conjunction with pro-biological cluster analysis techniques (Hierarchical, C-means, Self-organizing Maps (SOM), Learning Vector Quantization (LVQ) etc) variety of methods are used for example Probabilistic Neural Network (PNN), Adaptive Resonance Theory (ART), Artificial Neural Network (ANN), Fuzzy logic and fuzzy rules based algorithms (GA) etc.

1.6 Artificial Neural Network Method:

In these days, the application of artificial neural networks (ANNs) to the interpretation and classification of data has received increasing attention. The multi spectroscopic data analysis and optimization of the numerous parameters have an impact on ANNs performance. ANNs have also been used for predicting various features. The most

15

commonly used neural networks are by far feed forward multilayer neural networks. In such networks, the inputs are made of vectors encoding the spectra to be interpreted, while the output represents the presence or absence of structural features to be recognized. Two different simple architectures can be used for this purpose: mono- and multi-outputs. Mono-output networks are specialized networks which are trained to recognize only one particular structural feature, while multi-output networks are trained to recognize several structural features from a single input vector simultaneously.

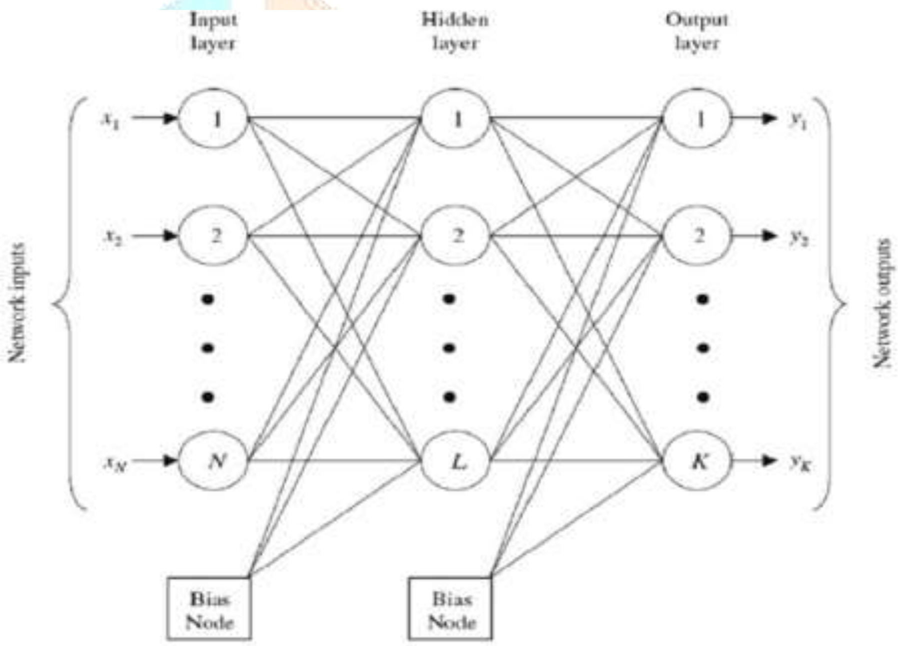


Figure 1.8 Schematic diagram of ANN

16

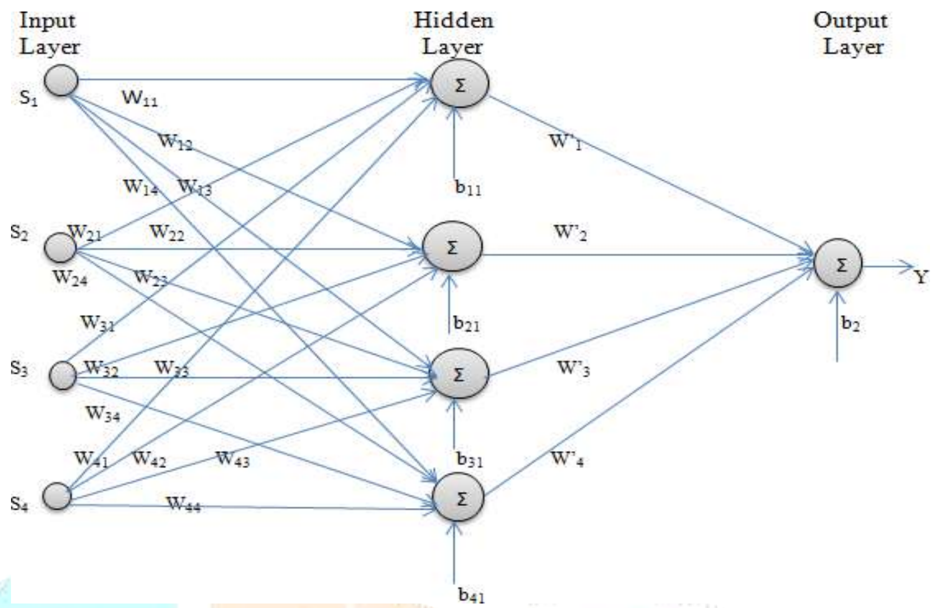


Figure 1.9 Single layer neural network

1.7 Ways to import neural network on hardware platforms

ANN can be created by any programming language like Mat lab, Python, lisp, STRIPS, Java, Octave, OCaml and Haskell. Deep learning algorithms can learn discriminative features directly from data such as images, text, and signals. These algorithms can be used to build highly accurate classifiers when trained on large labeled training data sets. Neural Network Toolbox supports training convolution neural network and auto encoder deep learning algorithms for image classification and feature learning tasks. Convolutional neural networks (CNNs) eliminate the need for manual feature extraction by removing features directly from raw images. This automated feature extraction makes CNN models highly accurate for computer vision tasks such as object classification. Neural Network Toolbox provides functions for constructing and training CNNs, as well as making predictions with a trained CNN model. Neural Network Toolbox includes command-line functions and apps for creating, training, and simulating neural networks. The apps make it easy to develop neural networks for tasks

17

such as classification, regression (including time series regression), and clustering. After creating your networks in these tools, you can automatically generate MATLAB code to capture your work and automate tasks.

We can create neural network in MATLAB. We got weight and bias matrices from this neural network design. We can design a neural network in Arduino by using these matrices data. The Arduino Uno is a microcontroller board based on the ATmega328. The Arduino Uno can be programmed with the Arduino software (Arduino IDE). The ATmega328 on the Arduino Uno comes pre burned with a boot loader that allows uploading new code to it without the use of an external hardware programmer. It communicates using the original STK500 protocol. We can also bypass the boot loader and program the microcontroller through the ICSP (In-Circuit Serial Programming) header. The ATmega8U2 firmware source code is available. The ATmega8U2 is loaded with a DFU boot loader, which can be activated by connecting the solder jumper on the back of the board (near the map of Italy) and then resetting the 8U2. We can then use Atmel's FLIP software (Windows) or the DFU programmer (Mac OS X and Linux) to load a new firmware or you can use the ISP header with an external programmer (overwriting the DFU boot loader).

1.6 Thesis Outline

Rest of this dissertation report is organized as follows:

Chapter 2 Literature review and problem statement, In this chapter the study of previous work and the theme of the thesis has been discussed which is taken up for further exploration.

Chapter 3 ANN and Materials/ Components Used, this chapter includes the data set which is used for design of artificial neural network. The basic idea of the ANN and its

18

structure are studied. Apart from this we also discuss the methodology used for implementing the classification of fish freshness.

Chapter 4: Implementation, this chapter we present novel algorithm which is implemented for sample collection and training neural network for sampled fish in our study in Matlab and demonstrate successful implementation of series of gas sensor array using Arduino Uno ATMega328.

Chapter 5: Result and Discussion, this chapter starts with description of the test environment setup and the physical configurations followed by the description of the dataset that is going to be used in this test. After that we present the result of the ANN and decide the quality of fish freshness.

Chapter 6: Conclusion and Future works, this chapter combines general conclusions of the thesis as well as some topics of relevant future works.

19

An Intelligent System for Fish Freshness Quality Assessment Using ANN

20

CHAPTER 2

2. LITERATURE REVIEW & PROBLEM STATEMENT

2.1 Review of Previous work:

Semiconductor gas sensor with partially overlapping selectivity has been used as gas detecting devices. One gas sensor alone can give no accurate statement concerning the type of gas, and the actual concentration occurred, due to the low selectivity of semiconductor gas sensors. Applying an array of semiconductor gas sensors in combination with Kohonen Feature Map (KFM) neural networks, unknown species of gases can be identified and quantified if the gas sensor system has been calibrated with this sort of gas earlier. The influence of different network parameters, e.g. the number of nodes in the network or the number of pattern vectors used to train the KFM to the learning and identification process have been studied [16].

Using semiconducting metal oxides and IR-absorption system, a sensor system for indoor air monitoring was proposed. To combine the functionality of semiconducting metal oxides and infrared absorption for gas detection, a new sensor system for a comprehensive indoor air monitoring is proposed. By the heated metal oxide gas sensor, the emission of infrared radiation and its propagation in the sensor system is modeled and experimentally validated. It is shown that even with the simple set-up of the system the infrared radiation can be used to detect indoor relevant CO_2 concentrations in the range of 1000 ppm with the IR system part. They reported that corresponding to the design and operation of the metal oxide gas sensor it detects explosive or toxic gas concentrations or volatile organic compounds in indoor applications [42].

It was reported the development of an array of eight different micro sensors based on Pd doped SnO_2 Nano crystalline sensing layers deposited by the sol-gel technology in the form of thick films on the top of Si-micro machine structures. At different relative 21 humidity levels the analyses of binary gas mixtures of CO and CH4 in air were investigated. PCA as pattern recognition (PARC) technique and PCR as multi variant analysis method have been applied to the input matrix that organizes in a vector way the response output of the sensors with the aim to identify and quantify the different binary mixtures. They reported that for the prediction of the real level of concentration of each component (CO and CH4) in mixture, especially for medium high concentrations of two gases, the PCR gave discrete results. They also proved the compatibility between the silicon micro machining technology for manufacturing micro machined substrates and the thick film technology, which produces high sensitive sensing elements [53].

It was investigated on CO/CH4 mixture measured with differently doped SnO2 sensors. The discrimination performances of array consisting of differently Pd doped SnO2 sensors operated at 350 and 4000C have been investigated. By using principle component analysis (PCA) and principle component regression methods, the sensor signals are evaluated. They reported that the array is able to discriminate between CO and CH4 in varying relative humidity conditions [34].

Broadly, ANNs are being used for two prime purposes viz. (i) Classification and/ or quantification of gases/odors and (ii) First for pre- processing of multi-sensor array data and then classification and/or quantification of gases/odors. In regard of ANNs are being used for classification and quantification of gases/odors attempted simultaneous classification and quantification of Hydrogen and Ammonia mixture at 15 different crisp concentration combinations using a three layer ANN to receive a lower degree of performance although it surpassed the performance they obtained using Partial Model Building [30].

For classification and quantification of H2, CH4, CO AND CO2, a modified multi-layer

Perceptron model with a three layer ANN using partially trained neural network was

22

used. Use of partially trained neural network approach improved the performance than that of fully trained ANN [21]. To feed a Self-Organized Map (SOM), a composed set of three parallel neural was also used. With this approach, SOM identified respective class and concentration of the considered gases/odors delivering a success rate of 80% [32].

Using two different ANNs, two different multi sensor array responses were processed and the performance was partially improved, for classification (identification) and quantification [37]. For monitoring carbon dioxide and relative humidity, Better generalization ability of two-stage neural network was also utilized. By processing the data each stage, quantification of relative humidity in seven crisp classes and gradual quantification of CO2 from 0 to 650 ppm was hence obtained facing variety of constraints and discordant reservations [38].

For identification of three classes of Chilean wines, the first PCA processed their primary data set and then trained and tested a neural network [29]. Using two principal components of SPCA transformed sensor array data; [30],[31] trained their neural classifiers for classification of considered gases/ odors. It was also employed 2 principal components of SPCA transformed sensor responses of 3 element sensor array for classification and quantification of binary mixture of two gases using a neural net [33].

2.2. Problem statement:

The following theme has been identified for further exploration and assessment by considering the literature and advancements in the e-nose system developments.

If the data used at stage I, belonging to different classes of fish are mutually uncorrelated, a simple ANN could perform better. For data transformation technique, Standard normalization is used. To learn normalize data transformation of raw data obtained from gas sensor array; a simple ANN may be trained. Thus, in stage I two cascaded ANN may be employed, where 1st ANN would nearly transform the raw data to its equivalent normalized values. From previous ANN for the identification of to their respective classes of gases/ odors, transformed data is obtained. Such methodology is improved classification performance.

24

CHAPTER-3

3. ANN & COMPONENTS USED

In this chapter we have discuss about ANN and various components which are used in our study viz. Gas sensor MQ-4,MQ-2, MQ-8,MQ-7,MQ-3and MQ-1353, Arduino is (main controlling device). Apart from this we also look into the software PLX-DAQ parallax used for taking real data implementing the This chapter also gives the basic idea of the ANN and its structure.

3.1. Artificial Neural Network

The progress of neurobiology has allowed researchers to build mathematical models of neurons to simulate neural behavior. This idea comes in 1940 when one of the first abstract models of neuron was introduced by McCulloch and Pitts(1943). Hebb in 1949 proposed a learning law that explained how a network of neurons learned. Some Other researchers pursued this notion through the next two decades, Such as Minsky in 1954 and Rosenblatt in 1958. Rosenblatt is credited with the perceptron learning algorithm and at the same time, Widrow and Hoff developed an important variation of perceptron learning know as the Windrow-Hoff rule.

In the middle 1980$_s$, the book Parallel Distributed processing by Rumerhalt and McClelland in 1986 generated great impacts on computer, cognitive and biological science. The back propagation algorithm developed by Rumerhalt,hinton and Williams(1986) offers powerful solution to training a multilayer neural network and shattered the cures imposed on perceptrons.A spectacular success of this approach is demonstrated bt the NETtalk system developed by Senowski and Rosenberg(1987), a

25

system that converts English text in to highly intelligible speech. It is interesting to note however that the idea of Back-propagation had been developed by Werbos (1974) and Parker in 1982.the symbolic approach which has long dominated the field of AI was recently challenged by the neural network approach.

3.2 Definition of Neural Network

A neural network is a computational structure composed of many interconnected elementary processing units called nodes or neurons by analogy with their biological counterpart. Each unit is very simple: it performs a weighted sum of the values received as inputs and applies a non-linear function (the transfer function) to lead to its output value. This output will be used as input to other units, and the organization of the connections between units defines the architecture of the network. The number of elementary units and their relationship will lead to the complex behavior of the network, which can be modified by adjustment of its internal parameters (the nodes weights and bias). Adjusting the network parameters to obtain the desired behavior is called training or learning. This process is carried out iteratively by a learning algorithm on a set of examples. The algorithm to be used for learning is a function of the type of the network. After the first works in the forties, studies on ANNs split off from their original goal: the modification of brain. ANNs are now widely used for their capability to memorize examples, perform classifications and associations, and build up an internal representation of a given problem, which can be used to perform generalization.

26

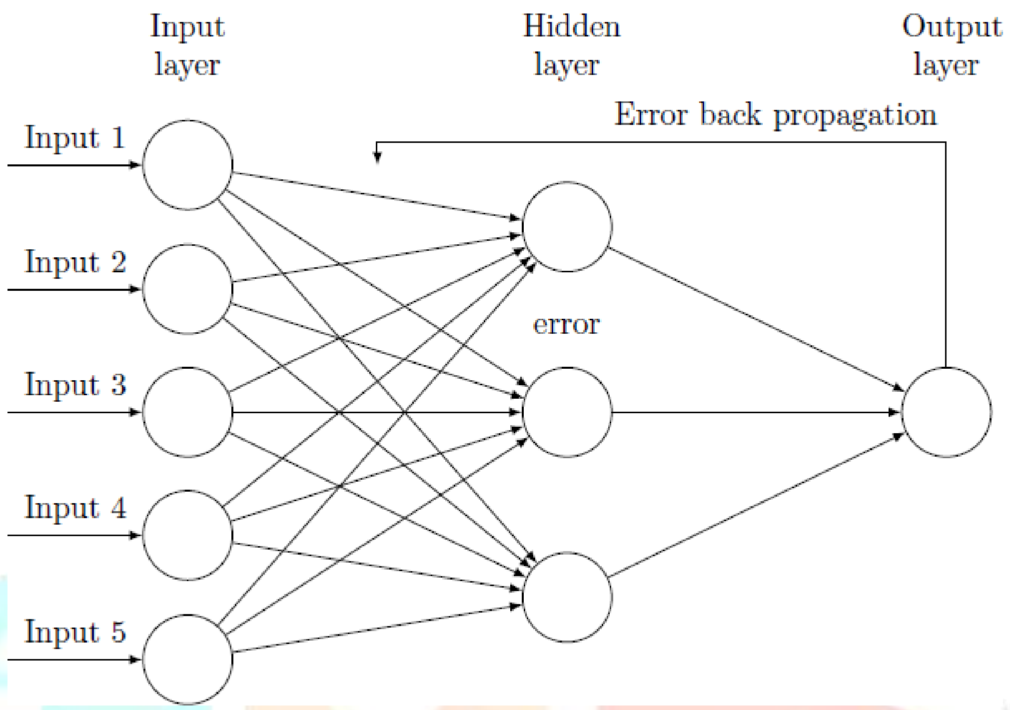


Figure 3.1 Basic Neural Networks

3.3 Feed Forward Neural Network

In feed forward neural network, the elementary processing units are stratified in different layers, in which each unit is connected to all the units in the previous and the next layer. The only purpose of the first layer, the input layer, is to receive the input data and to distribute it to the next layer. The last layer, the output layer or decision layer gives the outputs of the network. Other layers, if any, are called hidden layers. Information is propagated from input layer(s) through hidden layer(s) to output layer. The input data is used as the input vector, while output vector consists of numerical values representing the absence or presence of specific features as shown in figure.3.2

27

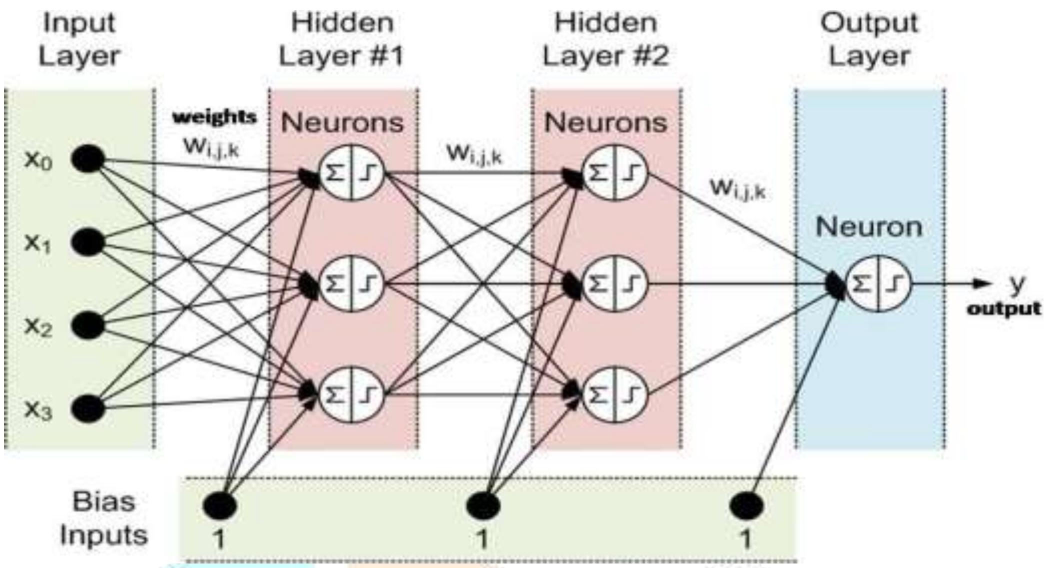


Figure 3.2 In FFNN, the data is propagated from inputs to outputs. It consists of 4 inputs, 2 hidden layers and one output.

There is no universally accepted rule to fix the number of hidden nodes: it has to be large enough to allow the building of a correct internal representation, but raising their number increases both the learning time and the risk of over-training. After random initialization of the network weights, the training is performed on a set of spectra associated with desired outputs (the training set) using a back propagation algorithm [9]. There are numerous variants of this algorithm, but they are all based on the same principle: the steepest descent minimization of the total error, calculated by the sum of absolute differences (or the squared differences) between network outputs and desired results for each output unit as shown in figure 3.3. Another set of examples (the test set) is used to determine the network efficiency. This set has to be distinct from the training set to measure the network capacity for generalization instead of its capacity for learning. Because the network builds up its internal representation on a set of examples, the size, and composition of this set will influence the learning efficiency. In fact, increasing the number of examples increases the overall performance of networks, but only up to a certain point. The effect of the composition is quite more subtle to grasp.

28

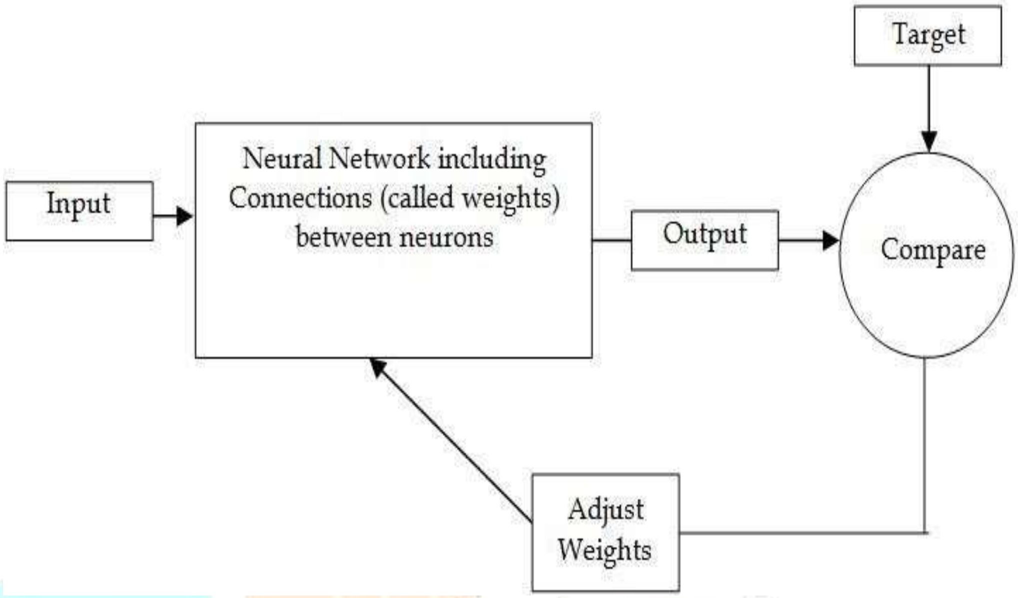


Figure 3.3 Neural Network in Supervised learning mode

The number of output nodes has significance. In fact, mono-output networks seem to perform better than networks with multiple outputs. Moreover, larger networks are harder to optimize than smaller ones (networks with fewer outputs). In fact, the best result for each output may occur at different training time. As a result, the network training will be stopped at a stage where performance is optimal for each output, but averaged. But for the determination of numerous structural features, the training and use of multiple mono-output networks are much more time consuming than for a single Therefore, advantages and drawbacks of using one single multi-output network are just opposite than those of using several mono-output networks. These considerations lead to suggest the use of a hierarchical system which should retain the better of the two approaches, in which Top-level neural network outputs leads to activate lower-level neural networks. So in this way we will have a dedicated network for each output.

29

3.4 Sigmoid functions as an Activation function

In a neural network, each neuron has an activation function which specifies the output of a neuron to a given input. Neurons are switches that output a _1‘ when they are sufficiently activated and a _0‘ when not. An activation function serves as a threshold, alternatively called classification or a partition. The purpose of an activation function in a Deep Learning context (i.e. multiple layers) is to ensure that the representation in the input space is mapped to a different space in the output. In all cases, a similarity function between the input and the weights are performed by a neural network. This can be an inner product, a correlation function or a convolution function. In all cases, it is a measure of similarity between the learned weights and the input. This is then followed by an activation function that performs a threshold on the calculated similarity measure. One of the activation functions commonly used for neurons is the sigmoid function. Sigmoid functions are often used in artificial neural networks to introduce nonlinearity into the model. A linear combination of the input is computed from the neural network signals and applies a sigmoid as an activation function to its result. This function is especially advantageous to use in neural networks trained by back-propagation algorithms. Because it is easy to distinguish, and this can interestingly minimize the computation capacity for training. The term sigmoid means _S-shaped‘, and logistic form of the sigmoid maps the interval (-∞, ∞) onto (0, 1) as seen in figure 3.3.

$$sig(t) = \frac{1}{1 + \exp(-t)}$$

30

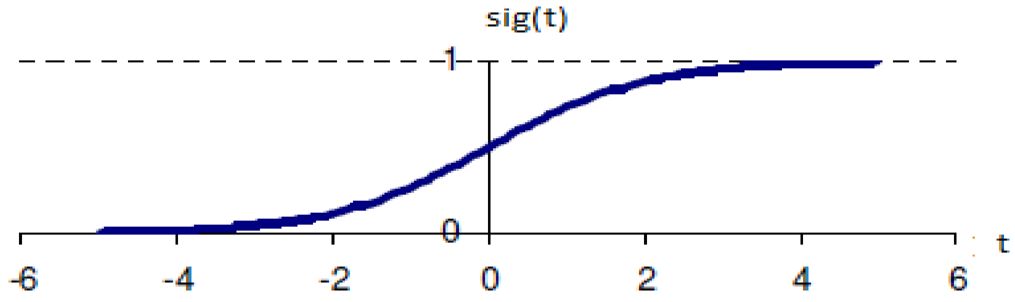


Figure 3.4 Sigmoid function looks like an _S‘.

Because the sigmoid function satisfies a property between the derivative and itself such that it is computationally easy to perform, is the main reason behind its popularity in neural networks Derivatives of the sigmoid function are usually employed in learning algorithms.

3.5 Back propagation Algorithm

The Backpropagation algorithm allows multilayer feed forward neural networks to learn input/output mappings from training samples. Backpropagation networks accustom itself to learn the relationship between the various set of example patterns, and similarly it could be able to apply the same relationship to new input patterns. The network should be able to focus on the features of random input. The activation function (e.g., sigmoid) is used to transform the activation level of a unit (neuron) into an output signal. The backpropagation algorithm always looks for the minimum of the error function in weight space using the gradient descent methodology. The combination of weights which tends to minimizes the error function is considered as a solution to the learning problem. Since this method requires computation of the gradient of the error function at each iteration step, we must guarantee the continuity

31

and differentiability of the error function. Obviously,we have to use a kind of activation function other than the step function.

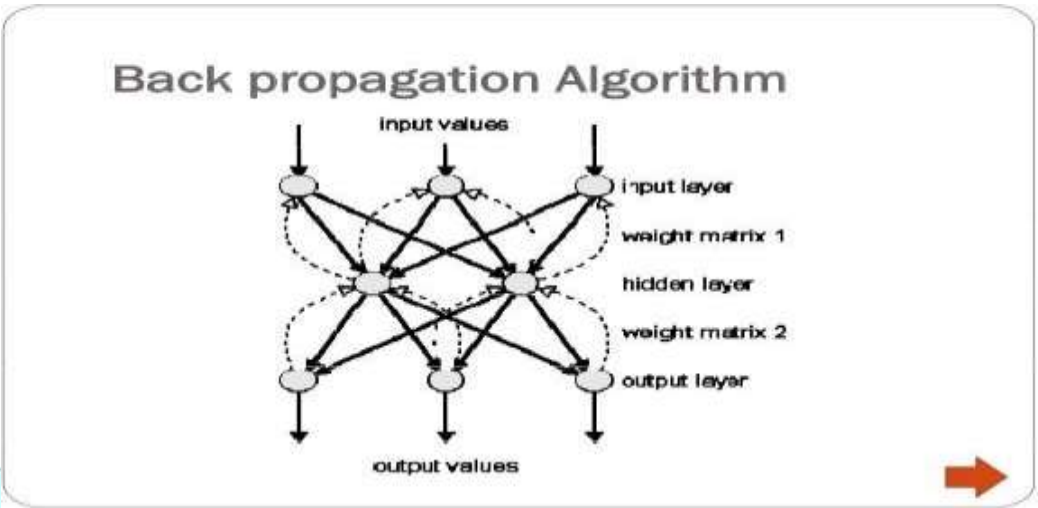


Figure 3.5 Back Propagation Algorithm

Consider a network consisting of single real input 'x' and network function 'F.' The derivative 'F'(x)' is processed in two phases:

Feed forward: the input 'x' is fed into the network. The essential functions of the nodes and their derivatives are evaluated at each node, and the derivatives are being stored.

Back propagation: The '1' is continuously fed into the output unit, and the network is run backward. The incoming information transmitted to a node is added up, and the result is multiplied by the value stored in the left part of the unit. The result is transmitted to the left of the unit. The result collected at the input unit is the derivative of the network function with respect to x [22].The algorithm works like this:

32

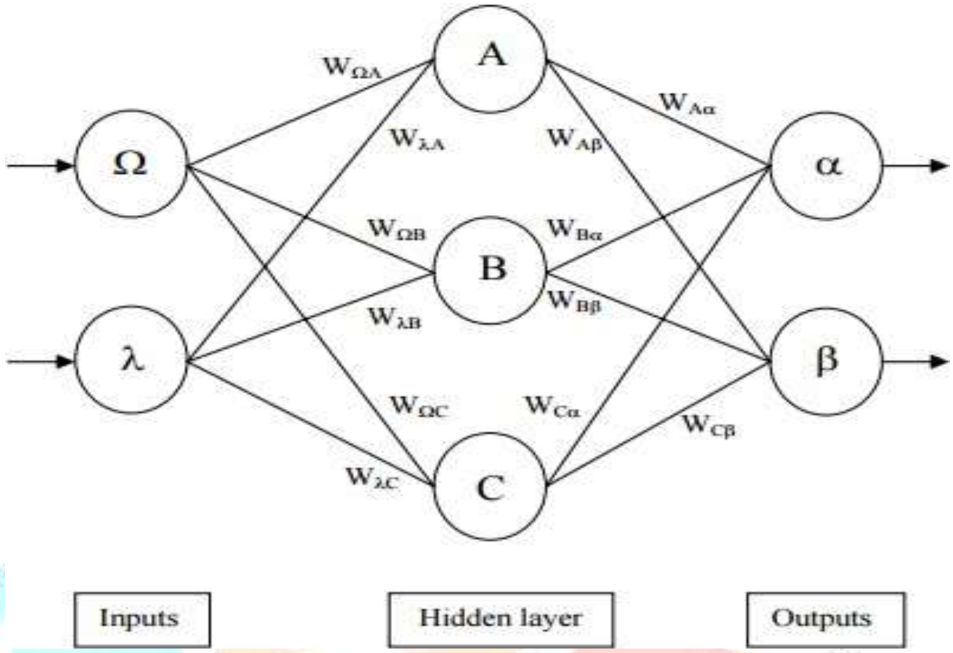


Figure 3.6 All the calculations for a reverse pass of Back Propagation.

1. Calculate errors of output neurons

   $\delta_\alpha = out_\alpha \, (1 - out_\alpha) \, (Target_\alpha - out_\alpha)$

   $\delta_\beta = out_\beta \, (1 - out_\beta) \, (Target_\beta - out_\beta)$

2. Change output layer weights

   $W^+_{A\alpha} = W_{A\alpha} + \eta\delta_\alpha out_A$ $\quad$ $W^+_{A\beta} = W_{A\beta} + \eta\delta_\beta out_A$

   $W^+_{B\alpha} = W_{B\alpha} + \eta\delta_\alpha out_B$ $\quad$ $W^+_{B\beta} = W_{B\beta} + \eta\delta_\beta out_B$

   $W^+_{C\alpha} = W_{C\alpha} + \eta\delta_\alpha out_C$ $\quad$ $W^+_{C\beta} = W_{C\beta} + \eta\delta_\beta out_C$

3. Calculate (back-propagate) hidden layer errors

   $\delta_A = out_A \, (1 – out_A) \, (\delta_\alpha W_{A\alpha} + \delta_\beta W_{A\beta})$

   $\delta_B = out_B \, (1 – out_B) \, (\delta_\alpha W_{B\alpha} + \delta_\beta W_{B\beta})$

   $\delta_C = out_C \, (1 – out_C) \, (\delta_\alpha W_{C\alpha} + \delta_\beta W_{C\beta})$

4. Change hidden layer weights

   $W^+_{\lambda A} = W_{\lambda A} + \eta\delta_A in_\lambda$ $\quad$ $W^+_{\Omega A} = W^+_{\Omega A} + \eta\delta_A in_\Omega$

   $W^+_{\lambda B} = W_{\lambda B} + \eta\delta_B in_\lambda$ $\quad$ $W^+_{\Omega B} = W^+_{\Omega B} + \eta\delta_B \, in_\Omega$

   $W^+_{\lambda C} = W_{\lambda C} + \eta\delta_C in_\lambda$ $\quad$ $W^+_{\Omega C} = W^+_{\Omega C} + \eta\delta_C in_\Omega$

The constant η (called the learning rate, and nominally equal to one) is put in to speed up or slow down the learning if required [23].

33

3.6 Supervised Learning Training Algorithms:

Supervised Learning Training algorithm include classical gradient-based methods and extensions both for sequential data and non-sequential. PyBrain also features the evolino algorithm, an SVM wrapper, and Gaussian processes.

3.6.1 Black-Box Optimization / Evolutionary Methods

Various black-box optimization algorithms have been implemented. In addition to various traditional evolution strategies, covariance matrix adaptation, co-evolutionary and genetic algorithms (including NSGA-II for multi-objective optimization), it has included recent new algorithms (not available in other libraries) such as natural evolution strategies, fitness expectation maximization and policy gradients with parameter-based exploration.

3.6.2 Reinforcement Learning

The reinforcement learning algorithms of PyBrain encompass basic methods such as SARSA, REINFORCE, and Q-learning, but also Natural actor-critic, neural-fitted Q-iteration, recurrent policy gradients, reward-weighted regression and state-dependent exploration.

3.6.3 Architectures Available

Architectures include recurrent neural networks and LSTM, standard feed forward neural networks, bi- and multi-dimensional recurrent neural networks & deep belief networks. The library puts the focus on, but is not limited to, (recurrent) neural network

34

structures arbitrarily structured as a directed non-cyclic graph of modules and connections.

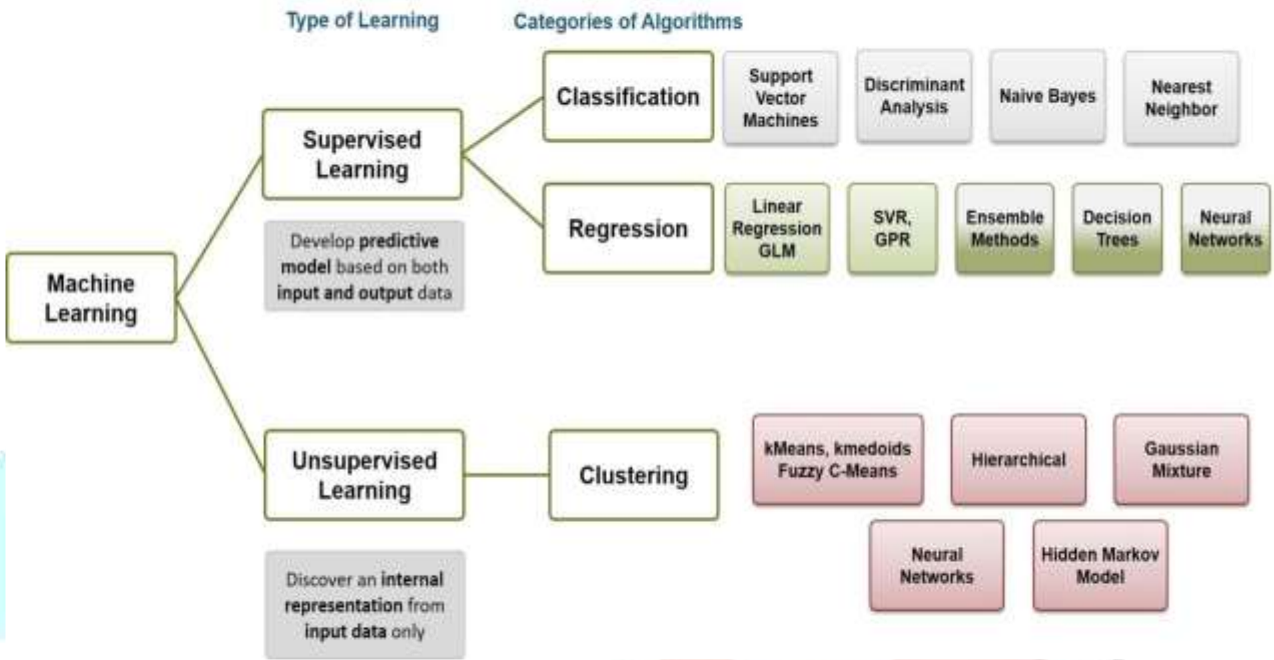


Figure 3.7 Categories of Supervised and unsupervised leaning

3.6.4 Compositionality

The basic structure of the library enables a structural approach to machine learning. Different types of algorithms and architectures can be connected and composed, and then used and trained as per desired. For example, consider arbitrarily structured recurrent neural network graphs that can be trained using various algorithms such as policy gradients, black-box search, and supervised learning. For example, both a deep belief network and LSTM architecture, though constituting different structures and architectures, can be trained by using the same gradient implementation (e.g., RPROP).

3.7 Components used

The system uses the following components for data gathering and analyzing –

35

1. MQ-4
2. MQ-2
3. MQ-8
4. MQ-7
5. MQ-5
6. MQ-135
7. Arduino At Mega 328(Microcontroller)

3.7.1 MQ-4 Gas Sensor

MQ-4 is High Sensitivity Gas methane (CNG) detector sensor. MQ-4 High Sensitivity Gas Methane (CNG) Detector Sensor Module which can sense the presence of Compressed Natural Gas (CNG), methane (CH4), etc. in the air. The module uses our MQ-4 sensor. It simplifies the interface to the odd pin spacing of the sensor and provides the interface through standard 4 x 0.1″ header pins. It provides an analog output corresponding to the concentration of the gases in the air and an easy to use digital output. The on-board potentiometer can be used to set the maximum gas concentration beyond which the digital output gets triggered. Just power the module with 5V set the threshold and you can start getting the gas concentration of the air around the sensor! An on-board LED signals the presence of any gases.The digital output can be easily interfaced to microcontrollers and other circuits. The analog output can be hooked up to an ADC of a microcontroller to get a wide range of sensor reading. The MQ-4 can detect natural gas concentrations anywhere from 200 to 10000ppm.

36

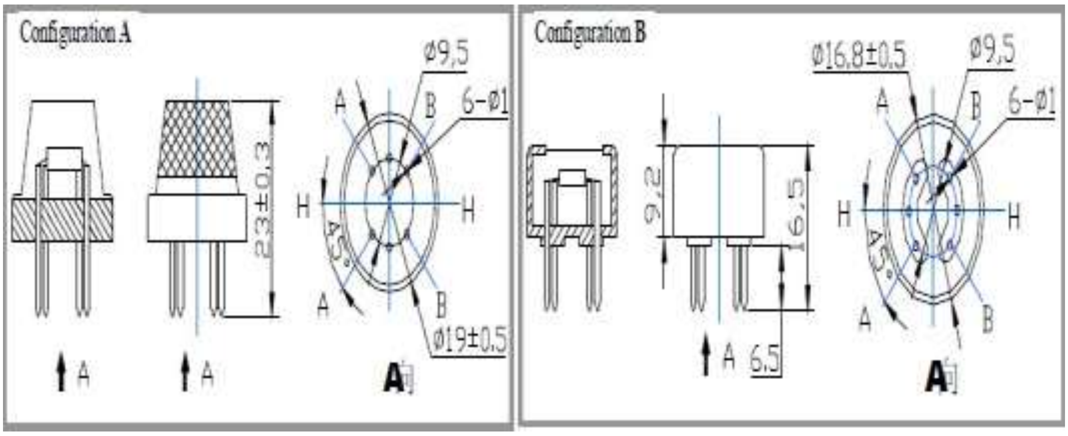


Figure 3.8 Gas Sensor Pin Configuration

Figure 3.9 MQ-4 Gas Sensor Circuit Diagram

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Figure 3.10 MQ-4 Gas Sensor

Structure and configuration of MQ-4 gas sensor is shown as Figure 3.8 (Configuration A or B), sensor composed by micro AL_2O_3 ceramic tube, Tin Dioxide (SnO_2) sensitive layer, measuring electrode and heater are fixed into a crust made by plastic and stainless steel net. The heater provides necessary work conditions for work of sensitive

37

components. The enveloped MQ-4 has 6 pin, 4 of them are used to fetch signals, and other 2 are used for providing heating current.

3.7.2 MQ-2 Gas Sensor

The MQ-2 is a Smoke LPG Butane hydrogen gas sensor. This is useful for gas leakage detection (Home & Industry)**.**It is suitable for detecting H2, LPG, CH4, CO, Alcohol, Smoke or Propane. Due to its high sensitivity and fast response time, measurement can be taken as soon as possible. The sensitivity of the sensor can be adjusted by potentiometer.MQ-2 gas sensor using gas sensitive material is to be clean air in the lower conductivity of Tin oxide (SnO_2).When the sensor when flammable gases are present in the environment in which the sensors conductivity with increasing concentration of combustible gas in the air increases. Use a simple circuit to convert the changes in conductivity and output signal that corresponds to the concentration of the gas.MQ-2 gas sensor higher sensitivity to liquefied petroleum gas, propane, hydrogen, detection of gas and other combustible vapors are ideal. This sensor can detect a variety of flammable gas, is a low-cost sensors for many applications.

Character Configuration:

1. Good sensitivity to Combustible gas in wide range
2. High sensitivity to LPG, Propane and Hydrogen
3. Long life and low cost
4. Simple drive circuit

Application:

1. Domestic gas leakage detector

38

2. Industrial Combustible gas detector
3. Portable gas detector

Figure 3.11 MQ-2 Gas Sensors

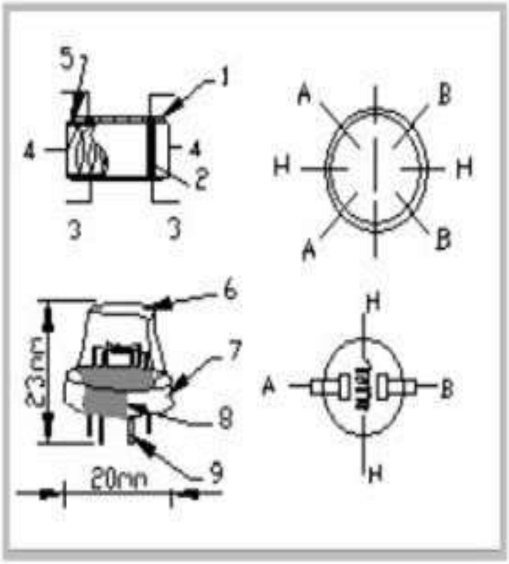
sensor composed by micro AL_2O_3 ceramic tube, Tin Dioxide (SnO_2) sensitive layer, measuring electrode and heater are fixed into a crust made by plastic and stainless steelnet. The heater provides necessary work conditions for work of sensitive components. The enveloped MQ-2 has 6 pin, 4 of them are used to fetch signals, and other 2 are used for providing heating current.

3.7.3 MQ-8 Gas Sensor.

MQ-8 is a semiconductor type gas sensor which can detect the gas leakage. The Sensitive material of MQ-8 is tin dioxide (SnO_2). It composed by micro Tin Dioxide (SnO_2) sensitive layer, AL_2O_3 ceramic tube, measuring electrode and heater are fixed into a crust made of stainless steel net and plastic.The heater provides essential work conditions for work of sensitive components. The enveloped MQ-8 have six pins, four of them are used to fetch signals, and other two are used for providing heating current as shown in figure[3.13] [31]. It has very low conductivity in clean air, Fast Response, Stable and long life, Simple drive circuit. MQ-8 Gas Sensor not only has sensitivity to propane and butane but also to other natural gasses, low sensitivity to cigarette smoke

39

and alcohol. This sensor can also be used for detection of other combustible gas such as methane.



	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

Figure 3.12 Structure and configuration of MQ-8 gas sensor.

The technical specifications of the sensor are as given below –

1. Circuit voltage – 5 V (0.1 V error permissible) AC or DC
2. Heating voltage – 5 V (0.1 V error permissible) AC or DC
3. Load resistance – 20K ohms
4. Heater resistance – 33 ohm (5% error permissible)
5. Heating consumption - less than 750 mW
6. Operating temperature - -10 to 50 (on Celsius scale)
7. Storage temperature - -20 to 70 (on Celsius scale)
8. Detecting concentration scope – 20 to 1000 ppm

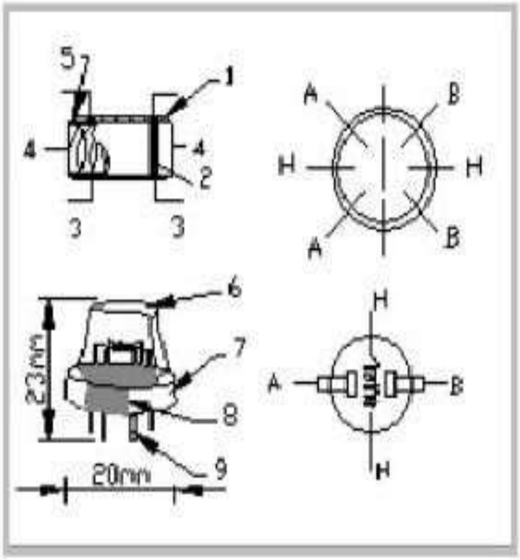
40

Figure 3.13 LPG (MQ-8) Sensor and pin outs

3.7.4 MQ-7 Gas Sensor

MQ-7 Gas Sensor has SnO_2 as a sensitive material, due to which it has excellent long term stability. It composed of micro AL_2O_3 ceramic tube, Tin Dioxide (SnO_2) sensitive layer, measuring electrode and heater are fixed into a crust made of stainless steel net and plastic [33]. The heater provides necessary work conditions for work of sensitive components .The enveloped MQ-7 have six pins, four of them are used to fetch signals, and other two are used for providing heating current as shown in figure 3.13 . MQ-7 has good sensitivity to Combustible gas in a wide range and High Sensitivity to Natural gas. They are mainly used in gas detecting equipment for carbon monoxide (CO) in family and industry or car.

41



	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

Figure 3.14 Structure and configuration of MQ-7 gas sensor

The technical specifications are as follows:-

1. Circuit voltage – 5 V (0.1 V error permissible)
2. Heating voltage (high) – 5 V (0.1 V error permissible)
3. Heating voltage (low) – 1.4 V (0.1 V error permissible)
4. Load resistance – can be adjusted
5. Heating resistance – 33ohms (5% error permissible)
6. Operating temperature - -20^{o} C to 50^{o}C
7. Storage temperature - -20^{o}C to 50^{o}C
8. Detecting range – 20 to 2000 ppm CO

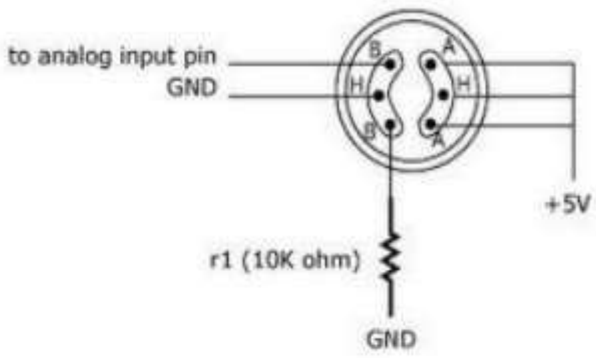


Figure 3.13 CO (MQ-7) Sensor and pin outs

42

3.7.5 MQ-5 Gas Sensor

MQ-5 is a Methane LPG Liquid Propane Gas Sensor Module are widely used in gas leakage detecting equipment‘s in family and industry, are suitable for detecting of LPG, natural gas , town gas, avoid the noise of alcohol and cooking fumes and cigarette smoke. The MQ5 (MQ-5) is used in gas leakage detecting equipment in consumer and industry applications, this sensor is suitable for detecting LPG, natural gas, coal gas. Avoid the noise of alcohol, cooking fumes and cigarette smoke. The sensitivity can be adjusted by the potentiometer. Sensitive material of MQ-5 gas sensor is SnO2, which with lower conductivity in clean air. When the target combustible gas exist, The sensors conductivity is more higher along with the gas concentration rising. Please use simple electro circuit, Convert change of conductivity to correspond output signal of gas concentration.MQ-5 gas sensor has high sensitivity to Methane, Propane and Butane, and could be used to detect both Methane and Propane. The sensor could be used to detect different combustible gas especially Methane, it is with low cost and suitable for different application

In the case of working with a MCU:

- VCC - 2.5V ~ 5.0V
- GND - Power Supply Ground
- AOUT - MCU.IO (analog output)
- DOUT - MCU.IO (digital output)

Specification and Features

1. Power supply needs: 5V

2. Interface type: Analog

43

3. Pin Definition: 1-Output 2-GND 3-VCC
4. High sensitivity to LPG, natural gas, town gas
5. Small sensitivity to alcohol, smoke
6. Fast response
7. Stable and long life
8. Simple drive circuit
9. Highly sensitivity to LPG, natural gas
10. Small sensitivity to alcohol, smoke
11. Fast response
12. Stable and long life
13. Simple drive circuit and Heater Voltage: 5.0V

	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

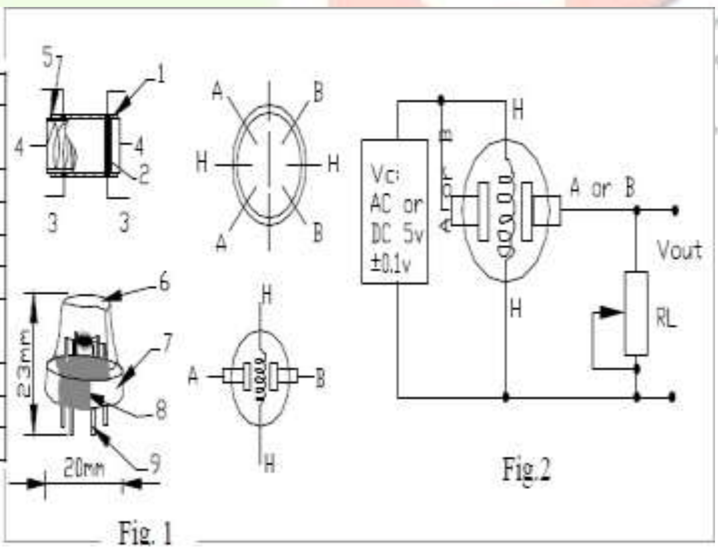


Figure 3.14 Electrical parameter & structure of MQ-5sensors

Structure and configuration of MQ-5 gas sensor is shown as Fig. 3.14 (Configuration A or B), sensor Composed by micro AL2O3 ceramic tube, Tin Dioxide (SnO2) sensitive layer, measuring electrode and heater are fixed into a crust made by plastic and

44

stainless steel net. The heater provides necessary work conditions for work of sensitive components. The enveloped MQ-5 have 6 pin,4 of them are used to fetch signals, and 2 for providing heating current. Electric parameter measurement circuit is shown as Figure.3.14

Figure 3.15 MQ-5 Gas Sensors

3.7.6 MQ- 135 Gas Sensor

The MQ 135 Air Quality Detector Sensor Module For Arduino has lower conductivity in clean air. When the target combustible gas exists, the conductivity of the sensor is higher along with the gas concentration rising. Convert change of conductivity to the corresponding output signal of gas concentration. The MQ135 gas sensor has high sensitivity to Ammonia, Sulphide and Benzene steam, also sensitive to smoke and other harmful gases. It is with low cost and suitable for different applications such as harmful gases/smoke detection

Specifications and features:

1. Air Quality Sensor Module
2. Condition: New
3. Size: 32mm X22mm X27mm

4. Main chip: MQ-135

45

5. Operating Voltage: 5V DC
6. Type: Analog & Digital
7. Sensitivity to Ammonia, Sulphide and Benzene steam
8. Detecting Range: 100-1000ppm
9. With signal output instructions
10. TTL output signal is low level
11. Analog 0 ~ 5 v voltage output, the higher the concentration, the higher the voltage
12. Color is showing pictures.
13. Sensitive for benzene, alcohol, smoke
14. Fast response and recovery
15. Adjustable sensitivity
16. Signal output indicator
17. Output voltage boosts along with the concentration of the measured gases increases

	Parts	Materials
1	Gas sensing layer	SnO_2
2	Electrode	Au
3	Electrode line	Pt
4	Heater coil	Ni-Cr alloy
5	Tubular ceramic	Al_2O_3
6	Anti-explosion network	Stainless steel gauze (SUS316 100-mesh)
7	Clamp ring	Copper plating Ni
8	Resin base	Bakelite
9	Tube Pin	Copper plating Ni

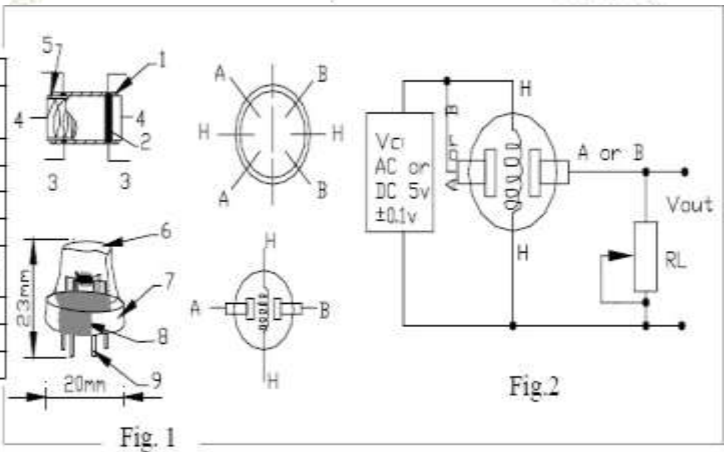


Figure 3.16 Electric parameter measurement circuits

46

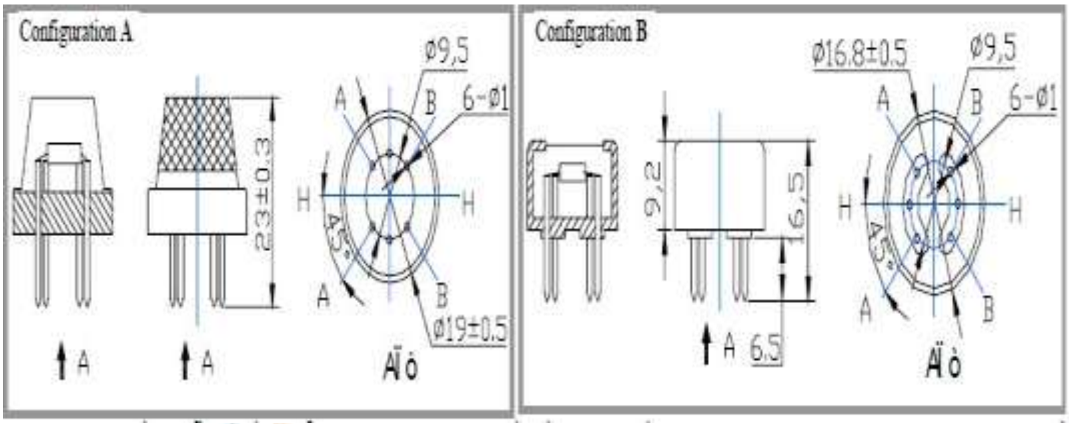


Figure 3.17 Configuration of MQ-135 sensors

Figure 3.18 MQ-135 sensor

Structure and configuration of MQ-135 gas sensor is shown as Fig. 1 (Configuration A or B), sensor composed by micro AL_2O_3 ceramic tube, Tin Dioxide (SnO_2) sensitive layer, measuring electrode and heater are fixed into a Crust made by plastic and stainless steel net. The heater provides necessary work conditions for work of sensitive components. The enveloped MQ-135 has 6 pin, 4 of them are used to fetch signals, and other 2 are used for providing heating current. Electric parameter measurement circuit is shown as Fig 3.16.

3.8 Arduino Uno Board:

Arduino is an open-source electronics platform based on easy-to-use hardware and software. Arduino boards are able to read inputs - light on a sensor, a finger on a button, or a Twitter message - and turn it into an output - activating a motor, turning on an

47

LED, publishing something online. The microcontroller can be programmed for what to do by sending a set of instructions. To do so we use the Arduino Programming language (based on wiring) and the Arduino software (IDE), the Arduino Software (IDE) based on processing. The Arduino software is easy-to-use for beginners, yet flexible enough for advanced users.

Table 3.1 Technical Specification of Arduino Uno AT Mega 328

Microcontroller	At mega 328
Operating Voltage	5V
Input Voltage (recommended)	7-12V
Input Voltage (limits)	6-20V
Analog Input Pins	6
DC Current per I/O Pin	40mA
DC Current for 3.3V Pin 50 mA	50 mA

Flash Memory	32 KB of which 0.5 KB used by Boot loader

48

SRAM	2KB
EEPROM	1KB
Clock Speed	16MHz

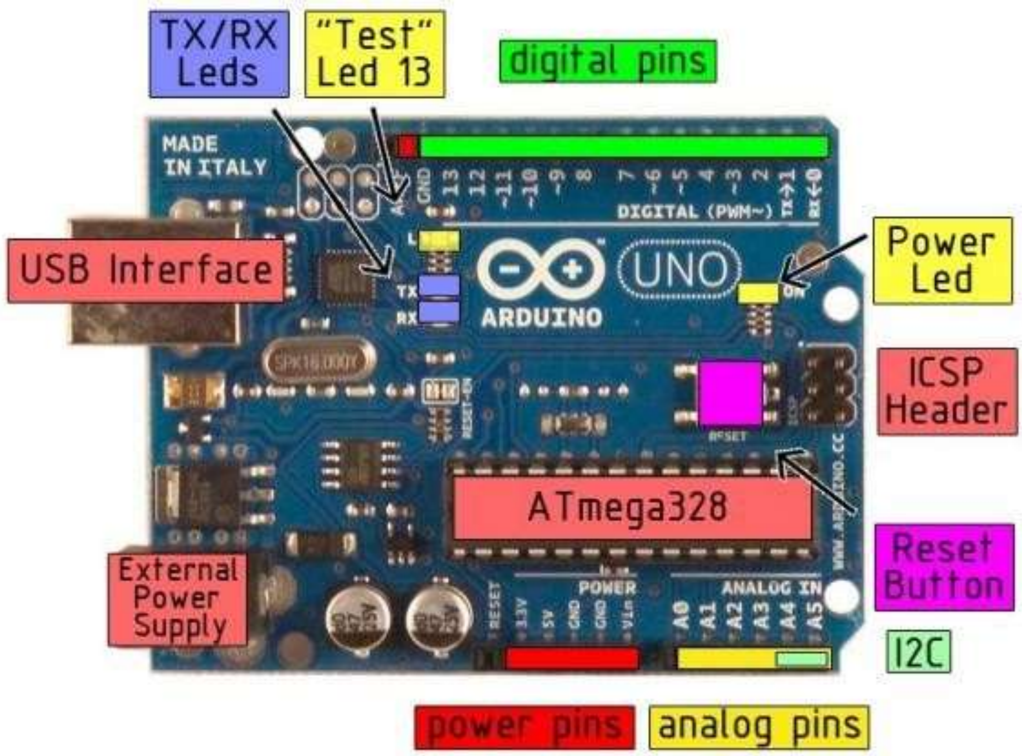


Figure 3.19 A typical Arduino Uno along with Board description

3.9 Programming Arduino

Once Arduino IDE is installed on the computer, connect the board with computer using USB cable. Now open the Arduino IDE and choose the correct board by selecting Tools>Boards>Arduino/Genuino Uno, and choose the correct Port by selecting Tools>Port. Arduino Uno is programmed using Arduino programming language based on

Wiring. To get it started with Arduino Uno board and blink the built-in LED, load

49

the example code by selecting Files>Examples>Basics>Blink. Once the example code (also shown below) is loaded into your IDE, click on the _upload' button given on the top bar. Once the upload is finished, we should see the Arduino built-in LED blinking.

Arduino Uno to ATmega328 Pin Mapping

When ATmega328 chip is used in place of Arduino Uno, or vice versa, the image below shows the pin mapping between the two.

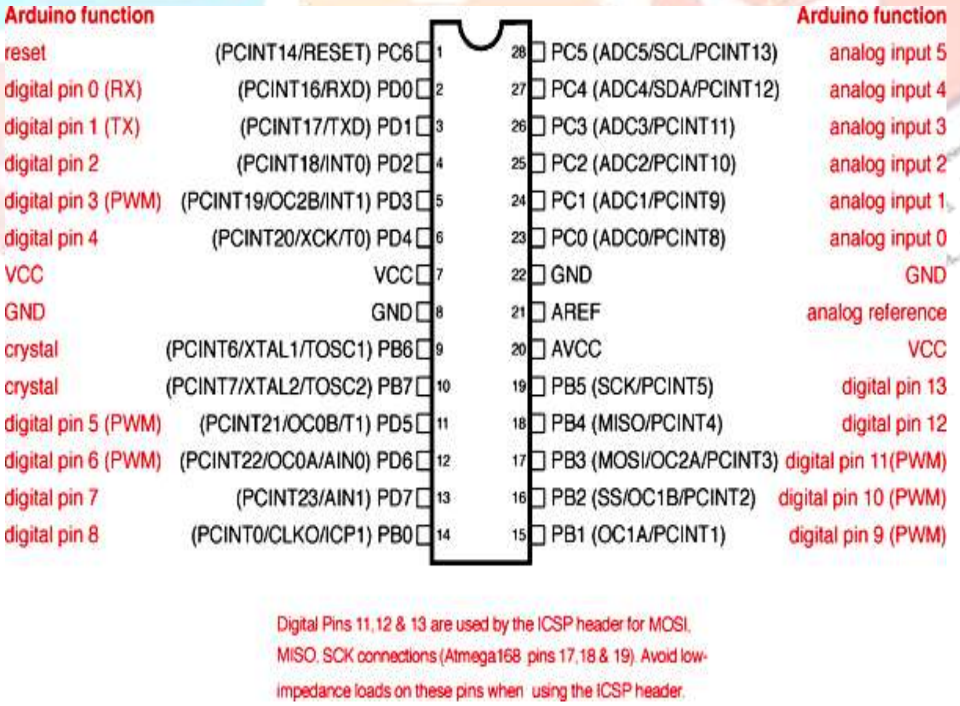


Figure 3.20 Arduino Uno Pin Mapping

50

3.10 Software Aspect:

The Arduino platform also provides software to program the Arduino microcontroller, as depicted in Figure 3.19 These instructions are written using the C++ programming language, which helps the development of programs (officially called sketches). The libraries provided by the Arduino IDE, simplify the creation of simple features such as reading or writing on a port, and it is also possible to import other libraries created by Arduino users for their projects, which helps the development of other users' projects. When buying a new Arduino expansion module for a project, the retailer provides the library containing the source-code, as well as some sketches to demonstrate how it works. However, being an open-source code, users can create their own libraries with some special features, or remove unused features to save flash memory, and then share it with the Arduino community. This open-source culture enables and encourages the creation of simple new products with the potential of truly improving people's lives. Besides the official software provided by Arduino, there are other alternatives that can improve productivity and also create a final product.

51

CHAPTER 4

4. EXPERIMENT IMPLEMENTATION

In this chapter we will describe the method and procedure for performing this experiment.

4.1 MQ Sensor Used and their Connections

In our Experiment we are using 6 sensors (MQ-4, MQ-2, MQ-8, MQ-7, MQ-5 and MQ-135) in parallel connection. Each sensor requires some preheating and it will take time approximately 2 or more hours. The voltage requirement of each sensor is +5volt.

Figure 4.1 Basic circuit configuration of MQ-sensor

52

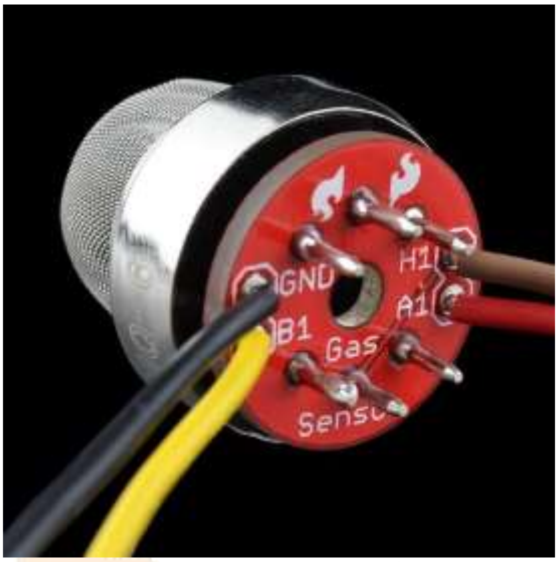


Figure 4.2 Way to Connect MQ-sensor

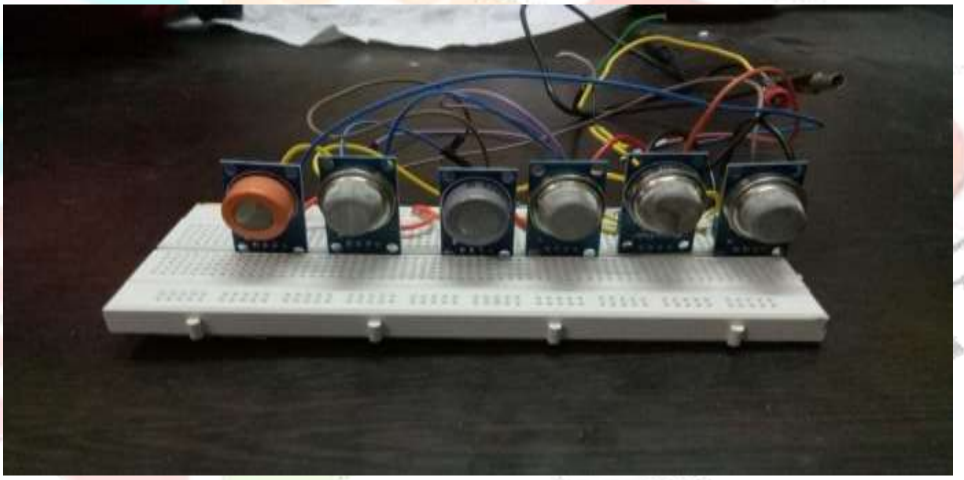


Figure 4.3 Six sensors connected together for experiment

4.2 Arduino Interfacing with MQ-sensors

Analog Input pin – The analog input pin of Arduino is internally a 10 bit ADC. The voltage output of the A_0 pin of the sensor is read by the analog input pin of Arduino. Now this voltage is converted to some digital value using internal ADC. The input voltage range from 0 to 5 volts will be converted to analog values between 0 to 1023. It takes about 100 microseconds (0.0001 s) to read an analog input, so the maximum reading rate is about 10,000 times a second. The output of the Arduino can be seen either on serial monitor or on excel sheet. The output of all six sensors will be parallel.

53

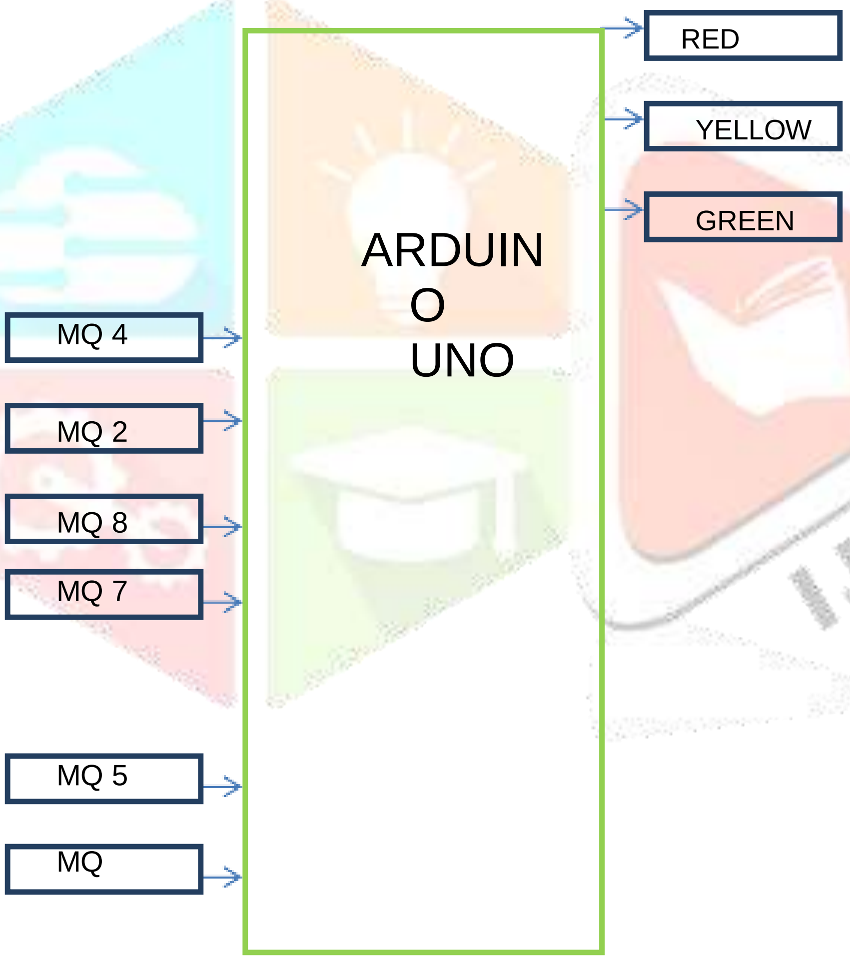


Figure 4.4 MQ Sensor Connections with Arduino

4.2.1 Programming Arduino

Once Arduino IDE is installed on the computer; connect the board with computer using

USB cable. Now open the Arduino IDE and choose the correct board by selecting

54

Tools>Boards>Arduino/Genuino Uno, and choose the correct Port by selecting Tools>Port. Arduino Uno is programmed using Arduino programming language based on Wiring. To get it started with Arduino Uno board and blink the built-in LED, load the example code by selecting Files>Examples>Basics>Blink. Once the example code (also shown below) is loaded into your IDE, click on the _upload' button given on the top bar. Once the upload is finished, We should see the Arduino built-in LED blinking.

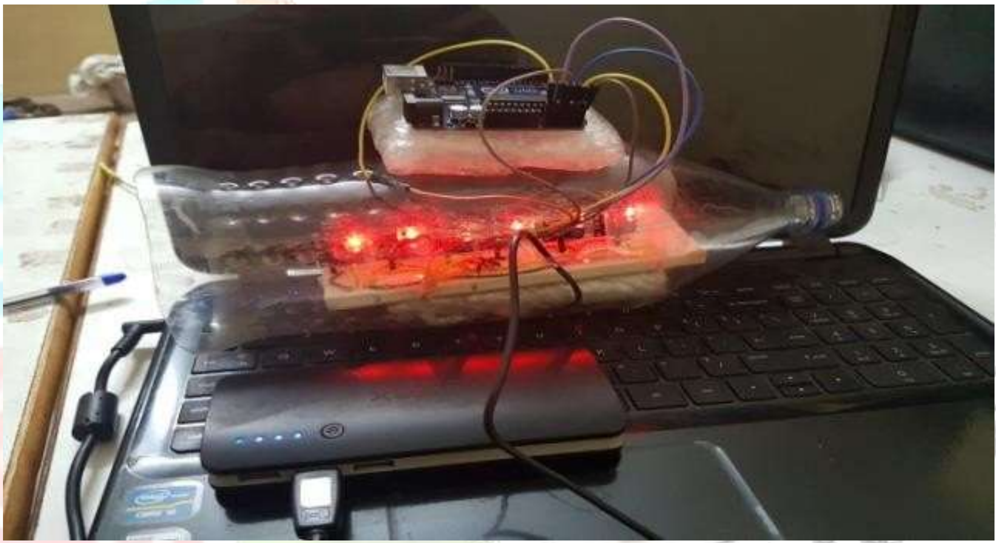


Figure 4.5 Complete working Model

Way the data collected from different fishes

For the collection of Fish data we made a working model, the model is consist of six sensors which are connected on a single breadboard. The breadboard is then inserted inside a cylindrical bottle and wires are taken out from a small hole from bottle. The model is then sealed so that no any unwanted gases come inside the bottle and also no any external effect occurs. The bottle is then proper packed and a small inlet is left from where Fish is bought near the mouth of hole through the sensors will sense the gases and data was captured. One by One different fishes were brought and data set was recorded for the training. Once the data was recorded then further we apply neural network to it. Firstly we bought Fish A (tilapia) than Fish B (Carpio) and lastly Fish C

55

(Tengra). Fresh (Day1), Semi Spoiled (Day 2) and Fully Spoiled (Day3) data set of fishes were collected and recorded.

Figure 4.6 Data Collected From Fish A (Tilapia)

Above diagram shows that how we collected the data from Fish A (Tilapia). Firstly the fresh data (Day 1) was collected and then (Day2) Semi Spoiled data set and lastly (Day 3) fully Spoiled data set was recorded for Tilapia fish.

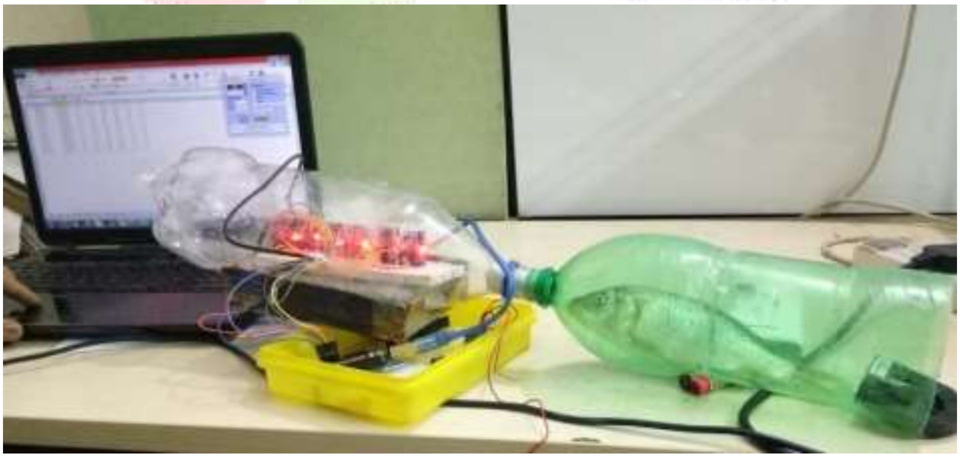


Figure 4.7 Data Collected from Fish B (Carpio)

56

Above diagram shows that how we collected the data from Fish B (Carpio). Firstly the fresh data (Day 1) was collected and then (Day2) Semi Spoiled data set and lastly (Day 3) fully Spoiled data set was recorded for Carpio fish.

Figure 4.8 Data Collected from Fish C (Tengra)

Above diagram shows that how we collected the data from Fish C (Tengra). Firstly the fresh data (Day1) was collected and then (Day2) semi Spoiled data Set and lastly (Day 3) the fully Spoiled data Set was recorded for Tengra fish.

4.3 Explanation Of data set

For this experiment we collected large number of samples from the different fish species. For training the Neural Network we collected around 100 suitable data set from all the samples of fishes of (Fresh, semi spoiled and spoiled) data were taken of each species. Out of these 100 samples 80 samples were taken for training and rest 20 is for testing. Few data sets of 100 samples are given below the table.

57

An Intelligent System for Fish Freshness Quality Assessment Using ANN

Table 4.1 Fish A fresh dataset (Day 1)

MQ-4	MQ-2	MQ-8	MQ-7	MQ-5	MQ-135
47	141	151	153	111	103
48	142	152	153	108	103
48	142	151	151	112	103
47	141	152	151	116	103
45	141	152	153	114	103
42	141	151	153	112	103
45	142	151	153	111	103
47	141	151	153	113	103
56	141	152	153	111	103
52	141	152	153	109	103
54	141	151	153	110	103
66	141	151	153	112	103
54	141	151	153	116	103
49	141	151	153	114	103
44	142	151	153	113	103
42	141	151	153	112	106
41	141	151	153	113	103
45	141	154	153	111	102
46	141	151	153	108	103
47	141	151	153	112	103
48	141	151	153	116	103
49	141	151	152	115	103

Table 4.2 Fish A Semi Spoiled data set (Day 2)

MQ-4	MQ_2	MQ-8	MQ-7	MQ-5	MQ-135
312	171	407	442	178	258
311	171	406	441	178	258
311	170	406	442	177	257
311	170	406	441	177	257
310	170	406	441	177	257

310	170	406	441	176	257

58

310	169	406	441	176	258
310	169	406	441	175	258
310	170	407	442	175	257
310	169	406	442	176	258
310	169	406	442	174	258
311	169	406	442	175	258
311	169	406	442	174	257
311	169	407	442	175	258
311	169	407	442	175	258
310	169	407	442	175	258
311	168	407	442	175	258
312	169	407	442	175	258
316	169	407	442	175	259
310	168	407	441	174	259
311	169	407	442	174	259

Table 4.3 Fish A Fully spoiled data Set (Day 3)

MQ-4	MQ-2	MQ-8	M8-7	MQ-5	MQ-135
359	617	413	721	512	489
359	617	413	721	512	489
359	617	413	721	512	489
360	617	413	721	512	489
360	617	413	721	512	489
361	617	413	721	512	489
361	617	413	720	512	489

361	617	412	720	512	489

59

363	617	413	721	512	488
363	617	412	720	512	489
363	617	413	720	512	488
363	617	413	719	512	488
364	617	413	719	512	488
365	617	413	719	511	488
365	617	413	719	512	488
365	617	413	719	512	488
365	617	413	719	512	488
364	617	413	719	512	488
364	617	413	719	512	488
364	617	414	719	512	487
365	617	413	720	512	488

Similarly the same way data of Fish B and Fish C can be taken and it will be given in appendix B and appendix C.

The responses of all sensors with respect to fish freshness are given below in graph. The horizontal axis represents serial number of samples as well as different states when fish was provided to the sensors. Vertical axis represents values of sensor output.

60

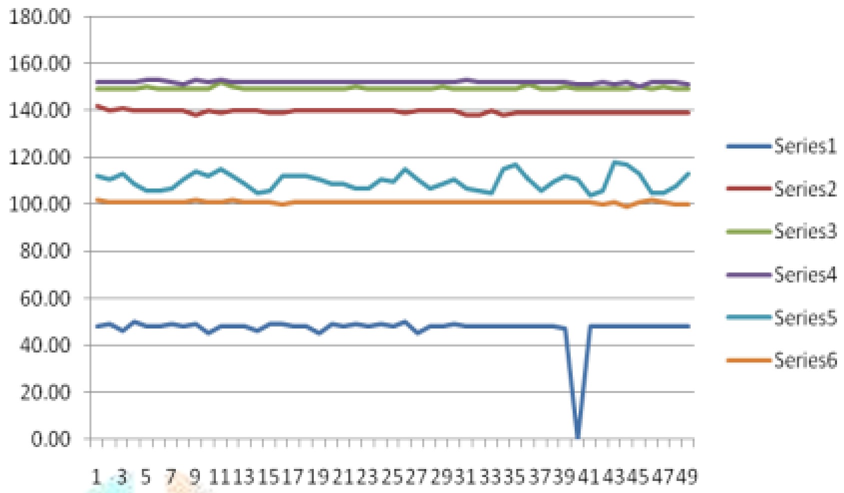


Figure 4.9 Day 1 Fish A Curve response of Data Set

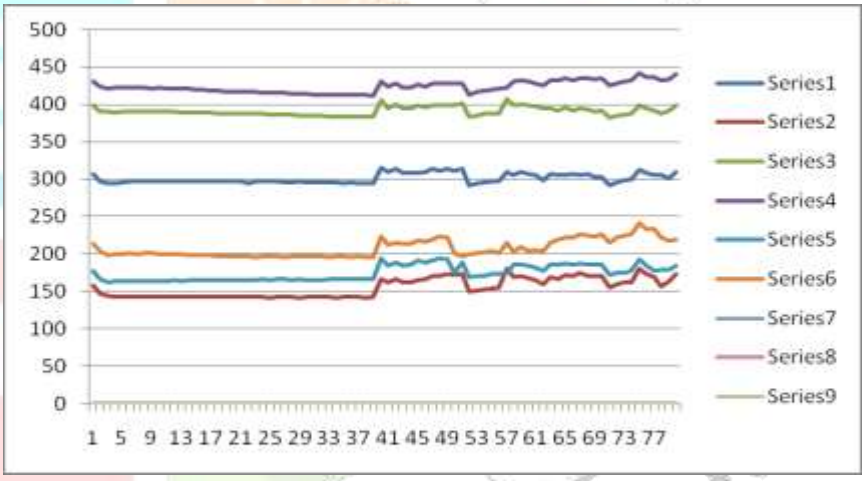


Figure 4.10 Day 2 Fish A Curve response of Data Set

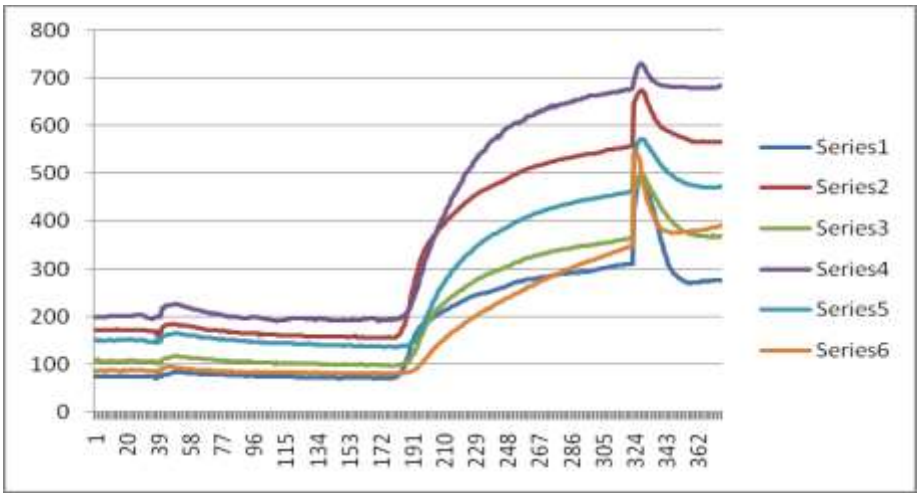


Figure 4.11 Day 3 Fish A Curve response of Data Set

61

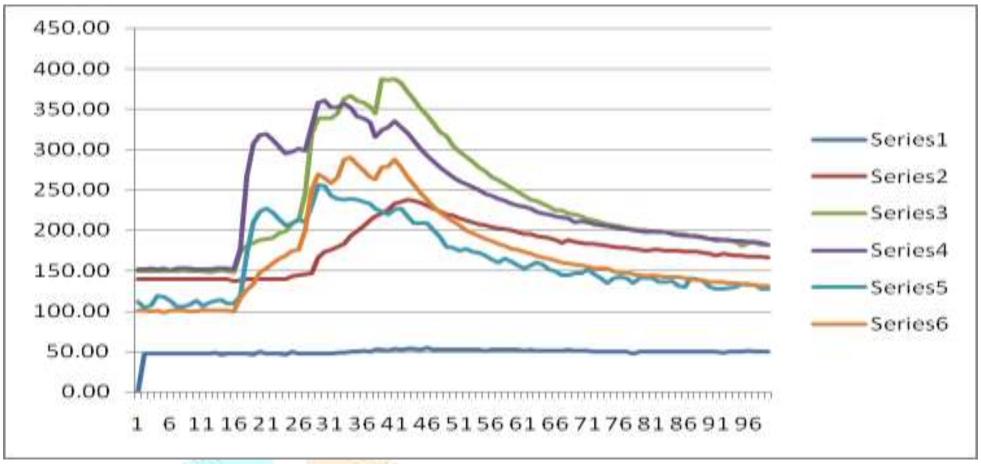


Figure 4.12 Day 1 Fish B Curve response of Data Set

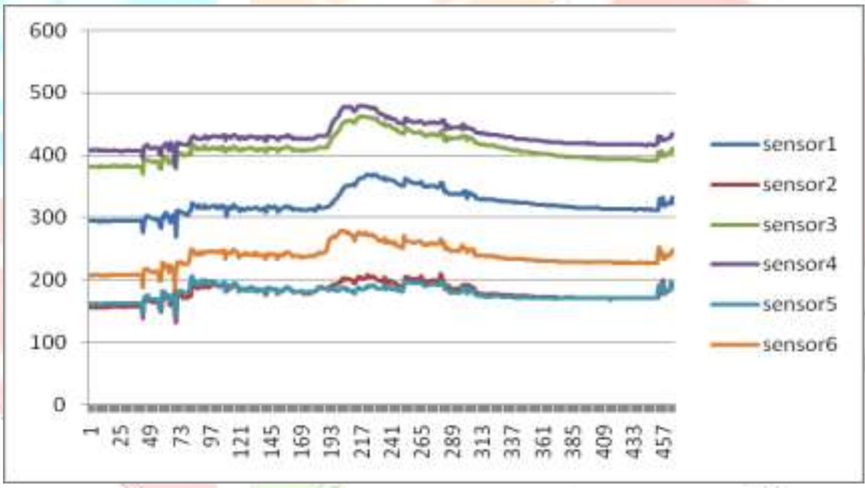


Figure 4.13 Day 2 Fish B Curve response of Data Set

62

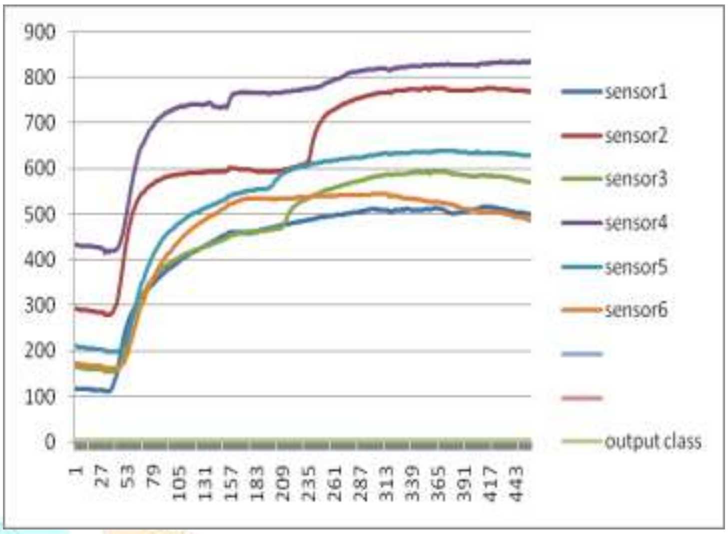


Figure 4.14 Day 3 Fish B (Carpio) response curve of Data Set

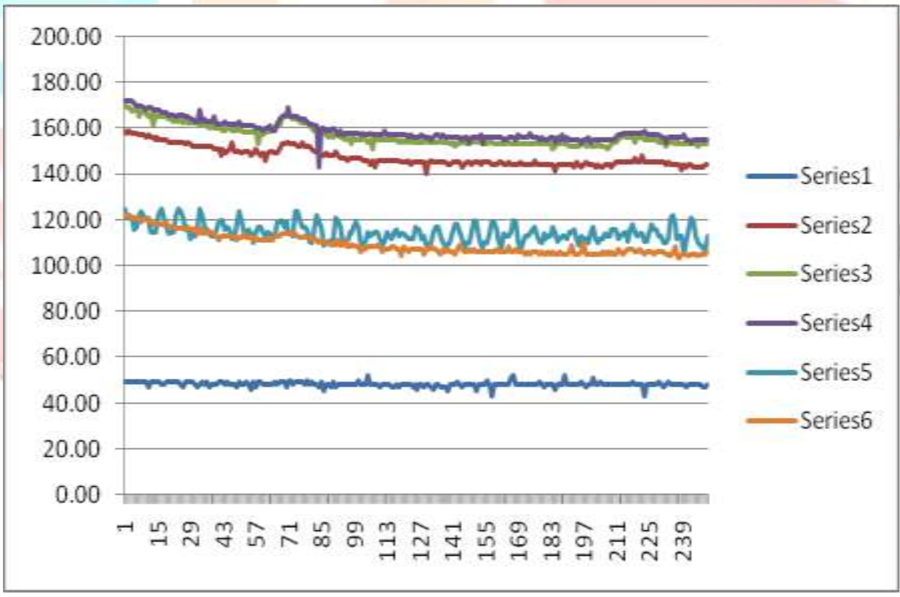


Figure 4.15 Day 1 Fish C (Tengra) response curve of Data Set

63

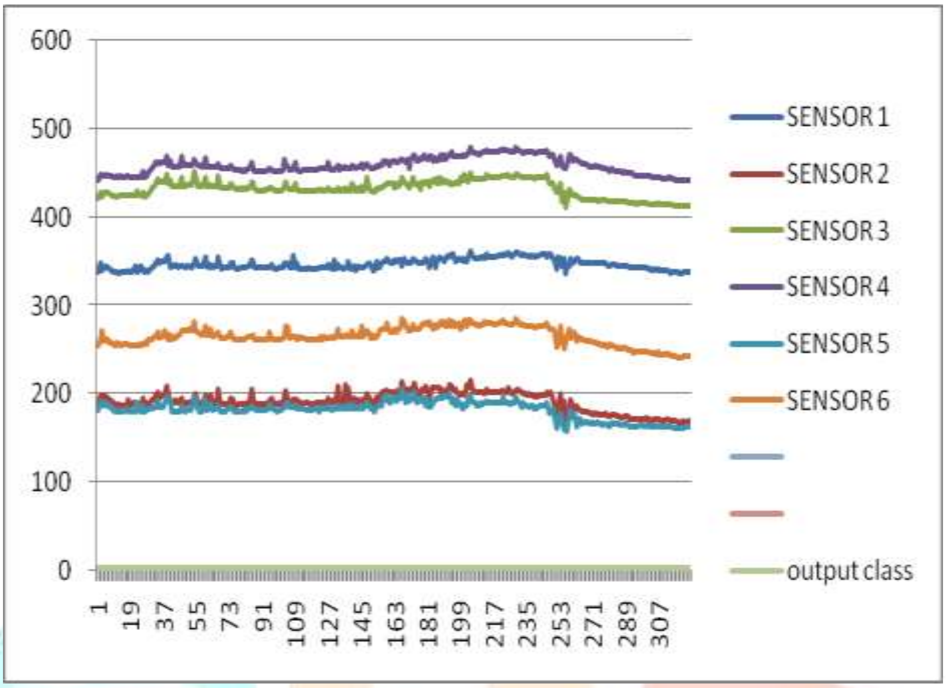


Figure 4.16 Day 2 Fish C (Tengra) response curve of Data Set

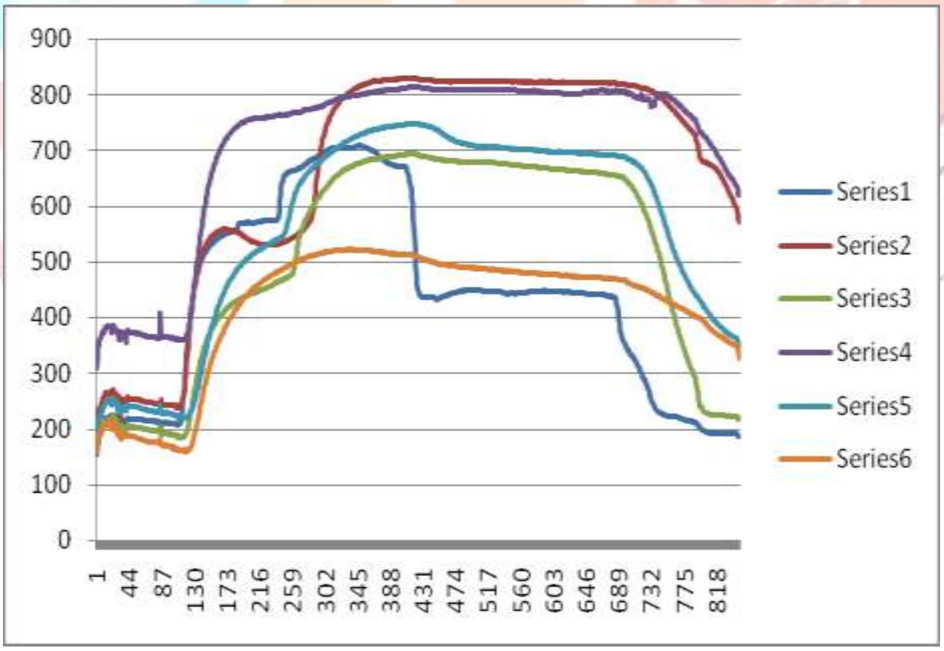


Figure 4.17 Day 3 Fish C (Tengra) response curve of Data Set

4.4 NETWORK TRAINING

4.4.1 Neural Network Training on MATLAB using Fresh (Day 1), Semi

Spoiled (Day 2) and Fully Spoiled data(Day 3):

64

There is approximately 410 data samples and more used for whole experiment. 80 samples classified per class. Out of 100 samples 80 samples of each class is used for training purpose and the rest 20 samples from each class is used for testing. In this experiment, we have used LN algorithm in which a neural network is designed and trained with DATASET FISH A (Day 1, Day 2, day 3), DATASET Fish B (Day 1, Day 2, day 3), ,DATASET fish C (Day 1, Day 2, day 3), for the detection of the Fish Freshness.

65

An Intelligent System for Fish Freshness Quality Assessment Using ANN

66

CHAPTER 5

5. RESULTS & DISCUSSION

This chapter starts with description of the test environment setup and the physical configurations followed by the description of the dataset that is going to be used in the t est. After that we present the result of the ANN i.e. mean square error, error while training the neural network and results on the Serial Monitor.

5.1Network trained with normalized data

The network is trained with 80 sampled values. Testing of network is done with 24 samples, 4 from each gas sensor response. Number of neurons in hidden layer is varied from 1 to 2 and performance is observed to find the optimum number of neurons. Optimum neurons obtained for hidden layer is 4. Architecture of the optimum network is shown in below figure. The training, testing and validation performance for optimum network is shown in Fig. 5.1.It is observed that MSE in the range of $10^{-15}$is obtained with training of raw data.

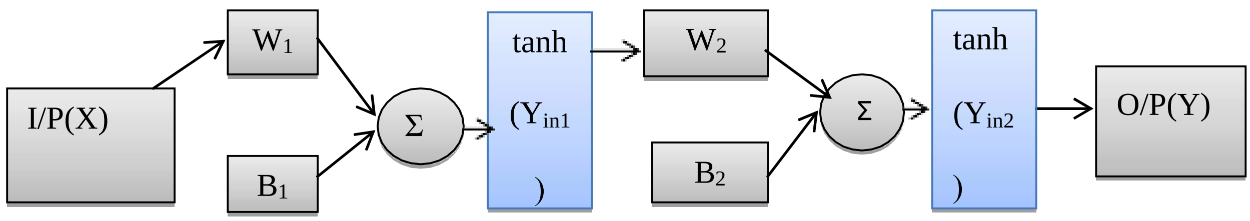


Figure 5.1 Architecture of optimum neural network for Normalized data

67

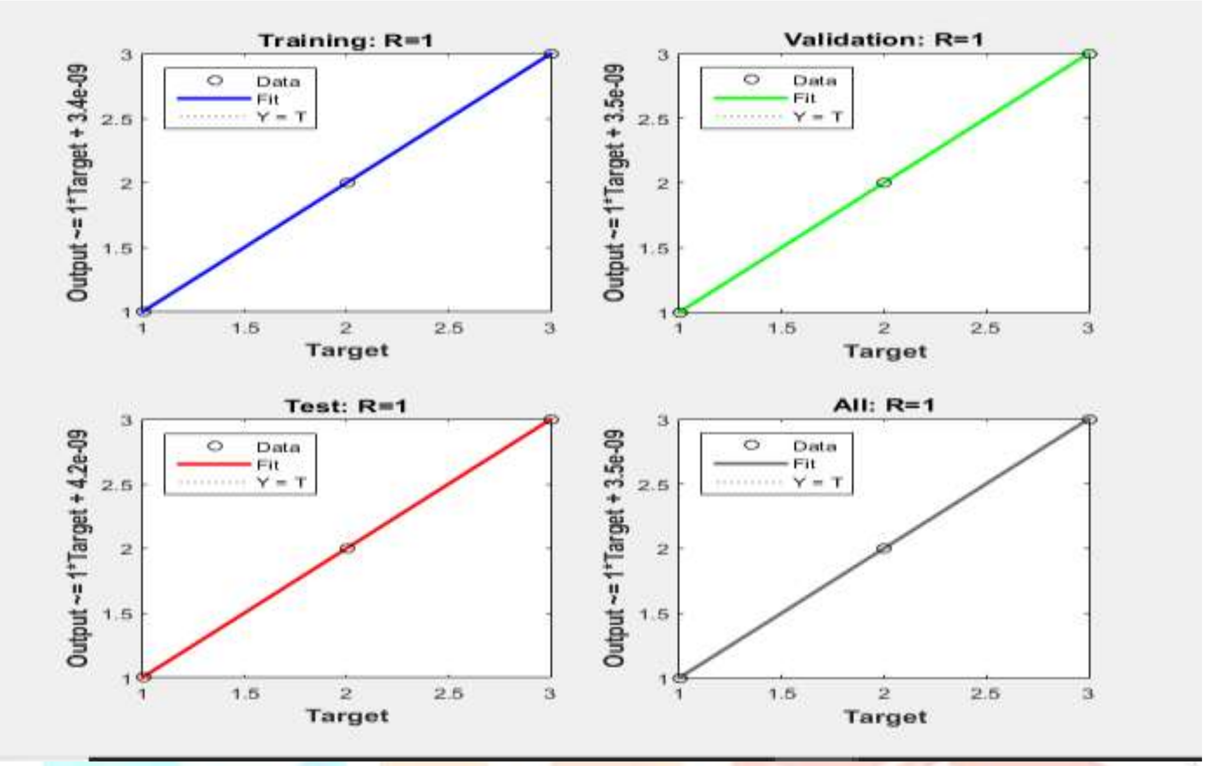


Figure 5.2 Regression plot using sensor‘ data of Fish A Tilapia

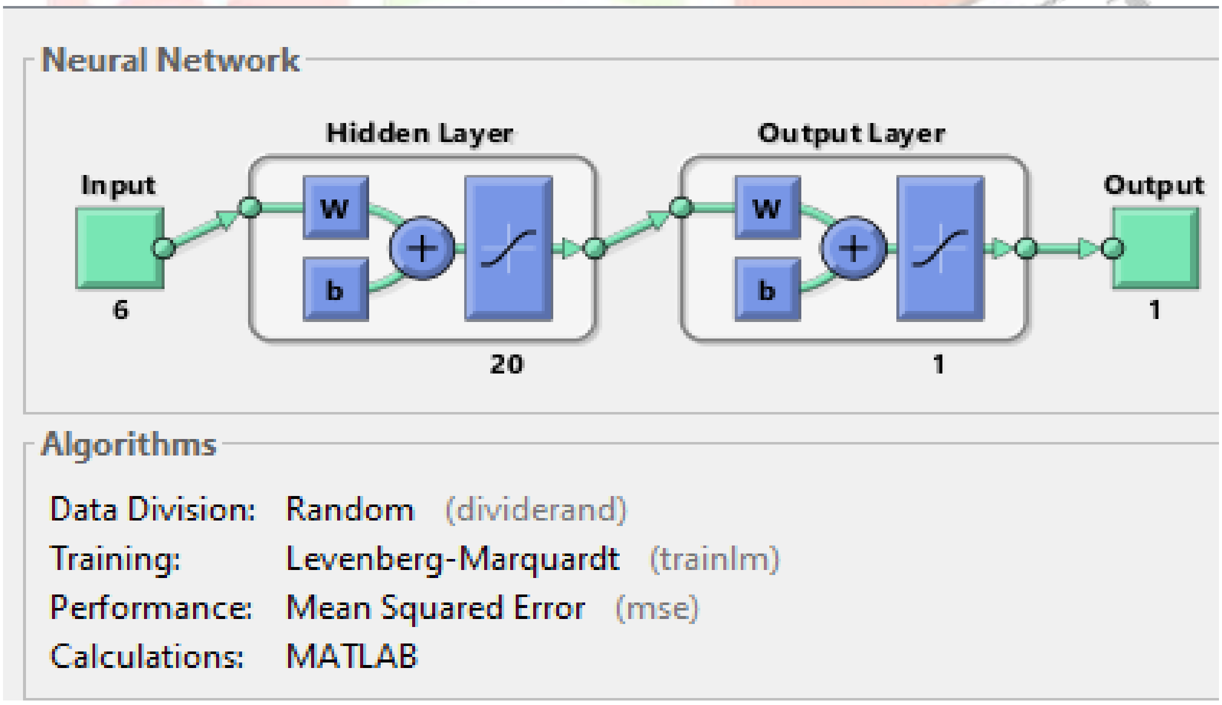


Figure 5.3 Schematic Applied Neural Network with different layer for Fish A Tilapia

68

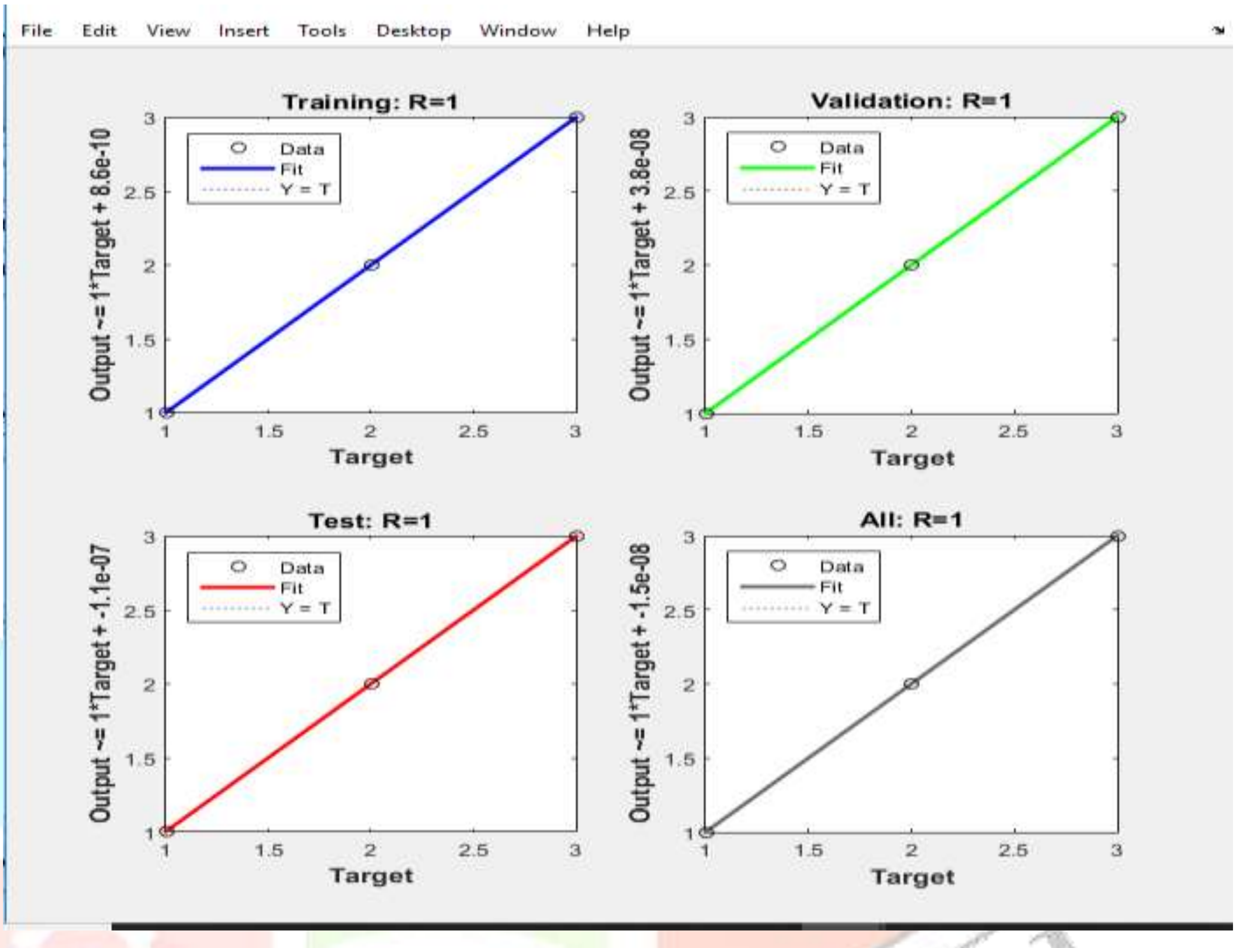


Figure 5.4 Regression plot using sensor‘ data of Fish B Carpio

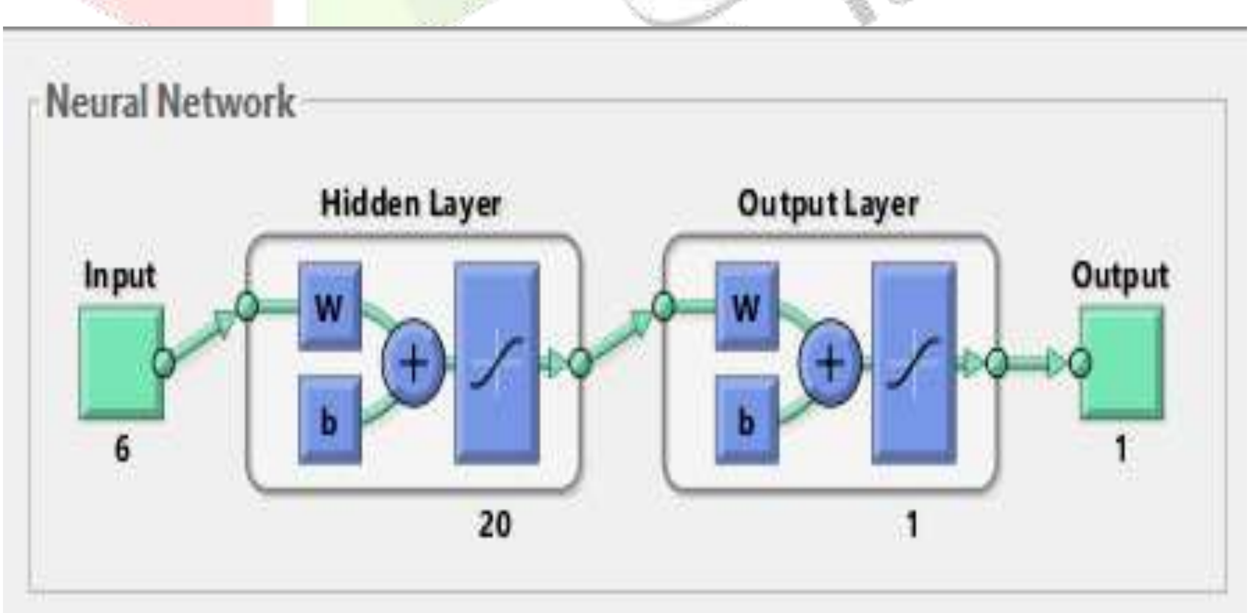


Figure 5.5 Schematic Applied Neural Network with different layer for Fish B

69

Figure 5.5

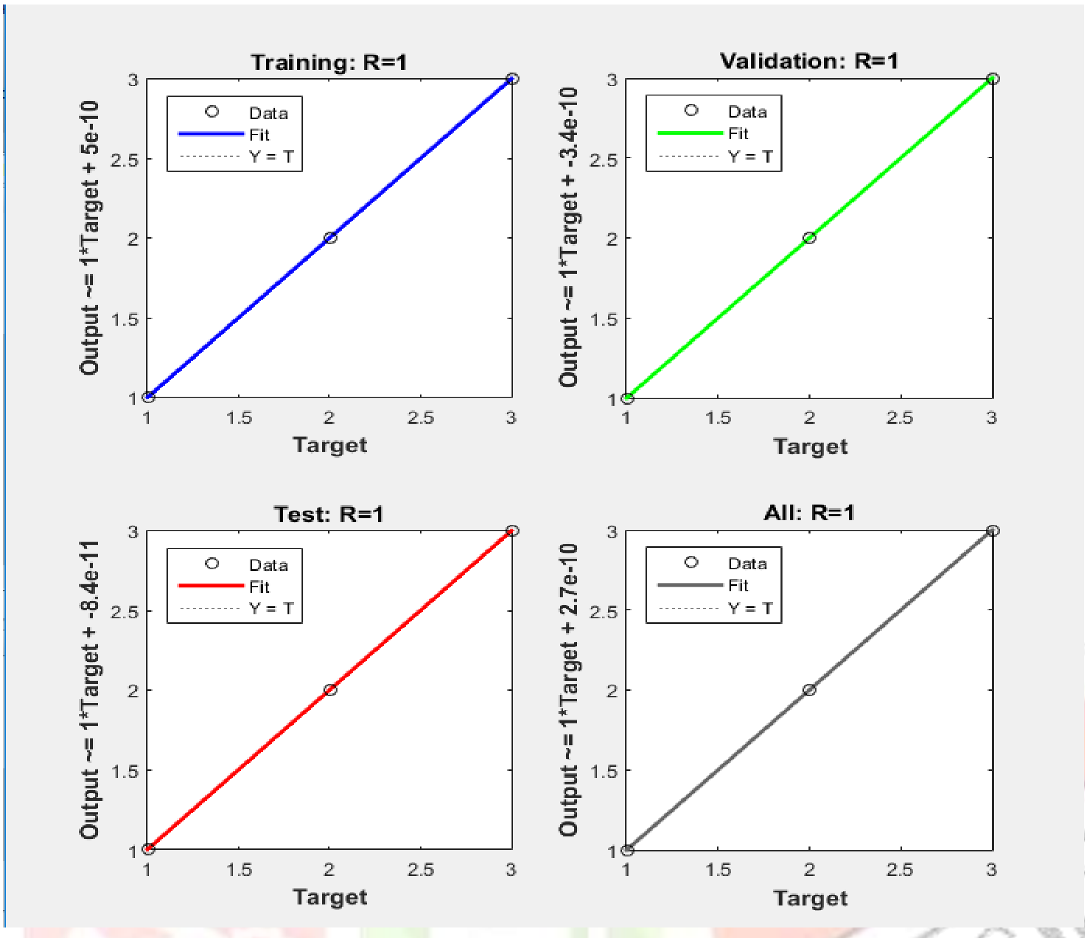


Figure 5.6 Regression plot using sensor‘ data of Fish C Tengra

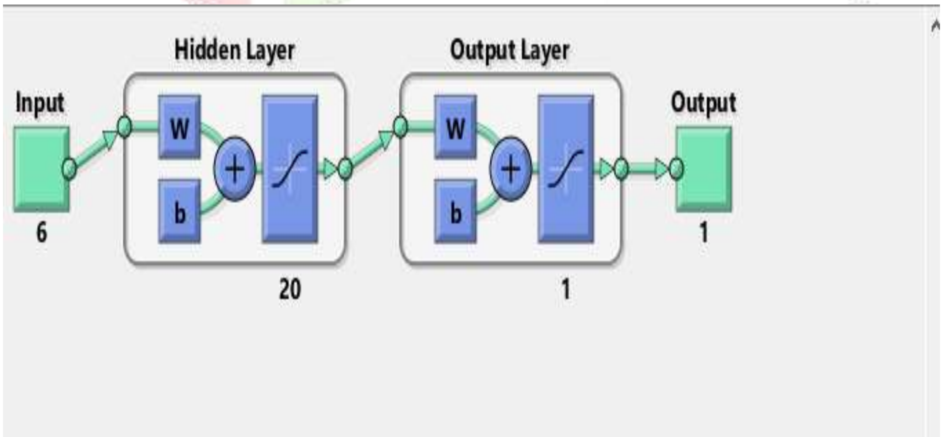


Figure 5.7 Schematic Applied Neural Network with different layer of Fish C Tengra

70

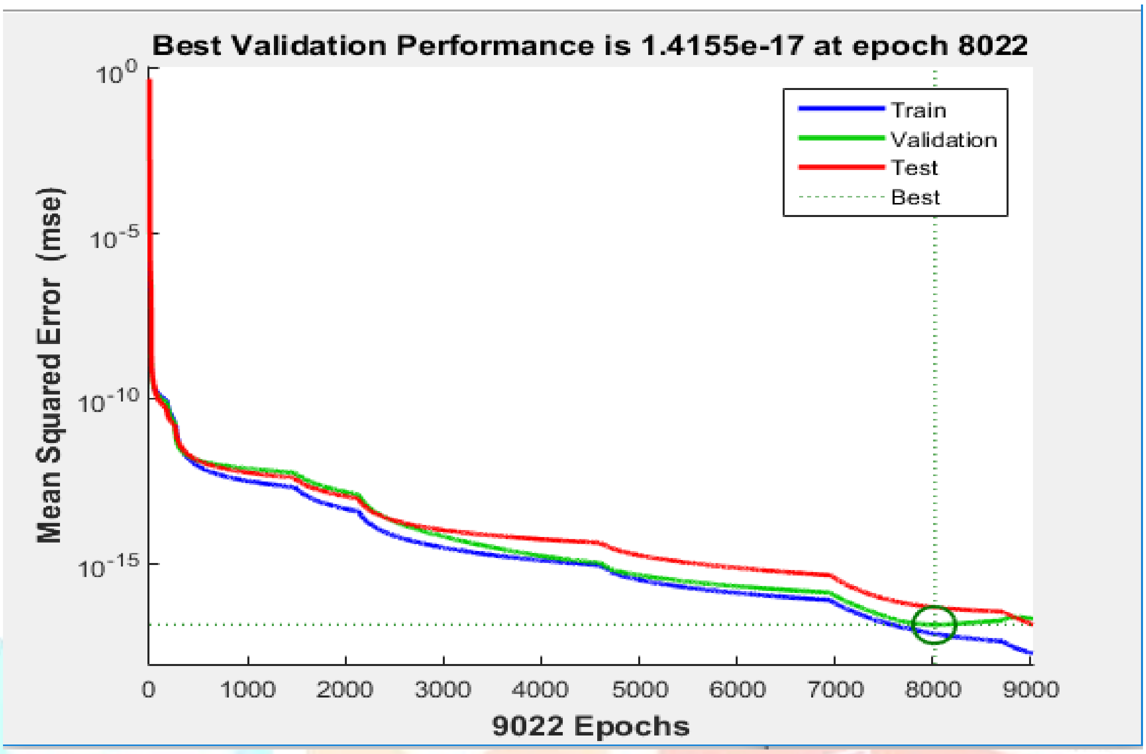


Figure 5.8 Performance plots of Fish A Tilapia

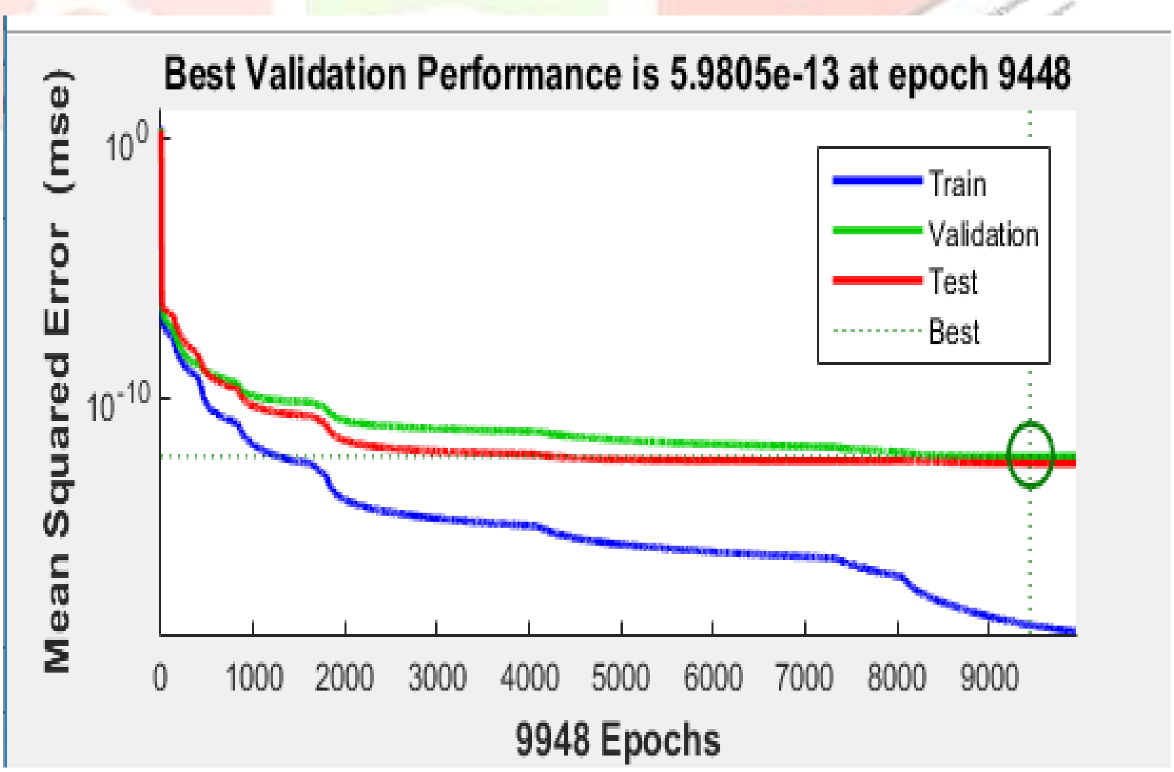


Figure 5.9 Performance plot of Fish B Carpio

71

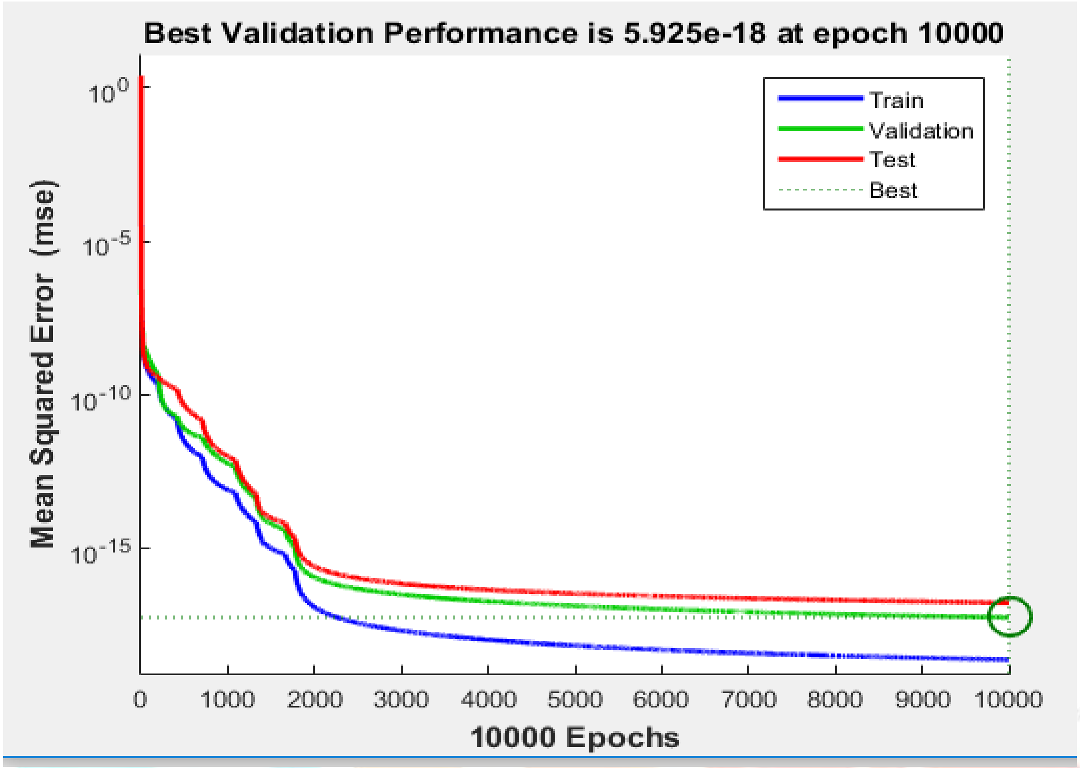


Figure 5.10 Performance plot of Fish C Tengra

5.2. Testing Sensor Node

In this thesis work all the experiments has done on Windows operating system. To check whether our Scalable Wired Sensor Network works efficiently or not, on the sensor node of the Arduino Uno At Mega 328. We have taken the sensor array response of the Sensors connected in series MQ-4, MQ-2, MQ-8, MQ-7, MQ-5 and MQ-135 to sense the data of Fishes i.e. Fish A(Tilapia) ,Fish B(Carpio) and Fish C(Tengra). We took responses of six sensors and then input responses to ANN. On the terminal window as shown in figure 4.1 we get a responses of sensor in ppm. The sensor response which is given at the ANNs, they are also directly stored in the text file for analysis.

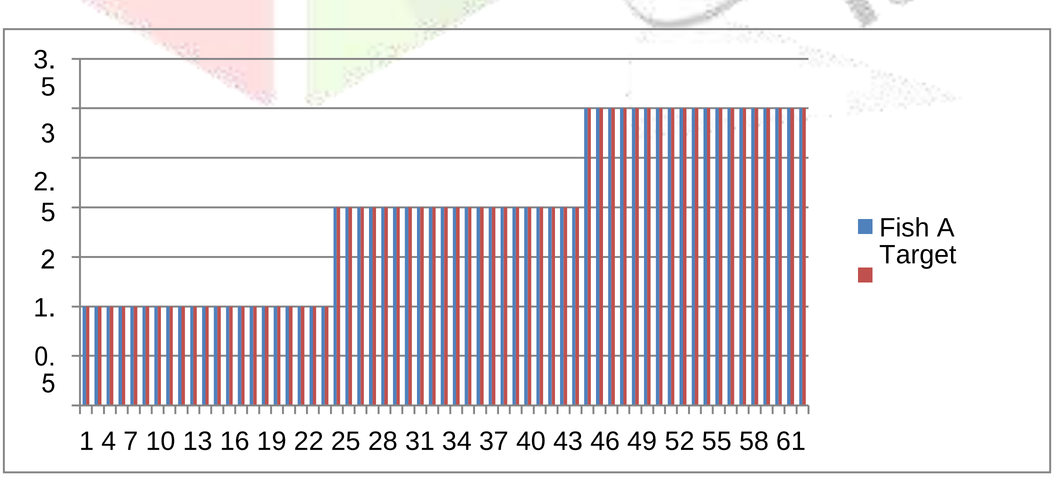
72

5.3. Result and Discussion

This sensor responses data shows that the Sensor Node is working properly. We have considered well classified data set for classification of Fish A Tilapia, Fish B Carpio and Fish C Tengra .The system has been designed to continuously monitor the data received from the Fishes Sensor Array. As shown in figure 4.2, the collected gas responses are processed by the neural networks. The ANN is successfully trained for classification of gas, using standard data set. Figure 4.3 shows the variation of neural network output from expected output while testing it with test data. The neural network has a mean square error value is 10^{-17} for Fish A (Tilapia), 10^{-13} for Fish B (Carpio) and 10^{-18} for Fish C (Tengra).

5.4. Comparison between Target output and Output using Neural Network

Fish A (Tilapia)

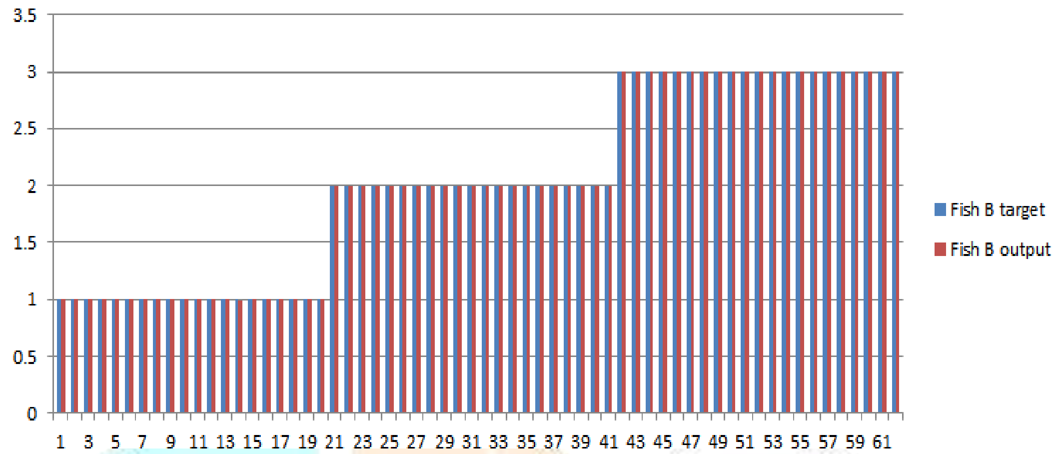


Number of samples

Figure 5.11 Comparison Of Target o/p & Output for Fish A(Tilapia)

73

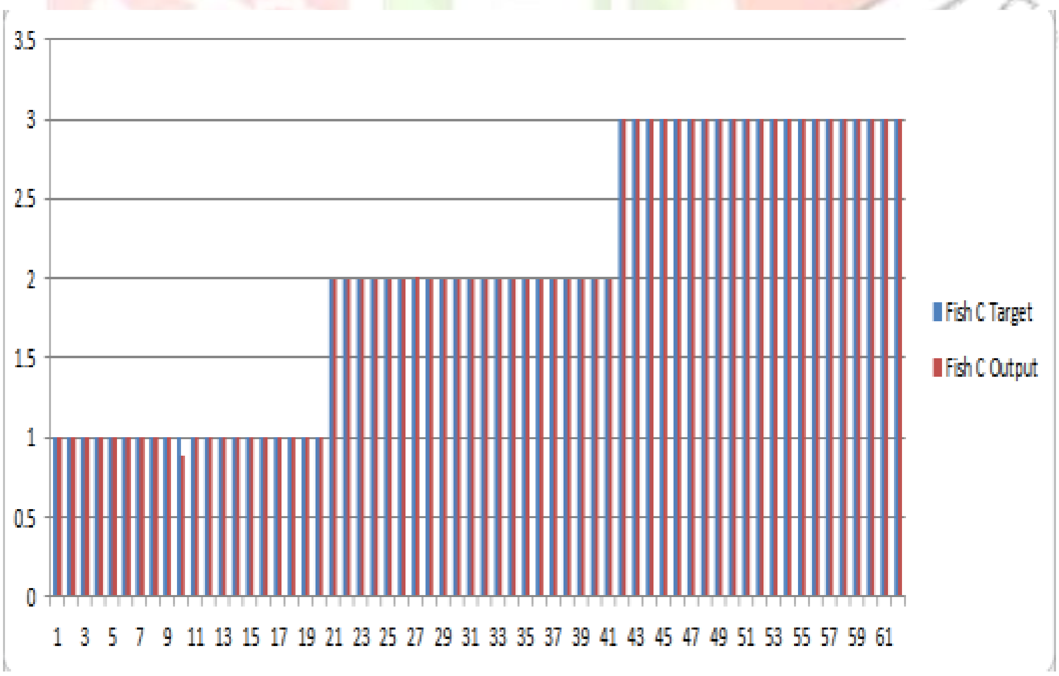
Fish B (Carpio)



Number of samples

Figure 5.12 Comparison Of Target o/p & Output for Fish A(Tilapia)

Fish C (Tengra)



Number of samples

Figure 5.13 Comparison Of Target o/p & Output for Fish A (Tilapia)

74

An Intelligent System for Fish Freshness Quality Assessment Using ANN

75

CHAPTER 6

6. CONLUSION & FUTURE SCOPE

6.1 Conclusion

This research work is a preliminary work to store and analyzed the sensor data using ANN. A group of sensor nodes are designed using Arduino AT mega 38 microcontroller Fish quality assessment detector is developed by using MQ2, MQ4, MQ5, MQ7, MQ8 and MQ-135 sensor. The design system consumption power is less and cheaper. In the future study, we expect that the our proposed work will be extended to more number of nodes so that they can identify more number of attributes .The experimental result show how the realized models give excellent result of fish freshness, the low percent of error committed in training and testing phase highlighted that absorption spectrum analysis combined with neural network models was the decisive choice to solve the problem.

The work undertaken has deal with Fish quality assessment from fish samples using statistical learning. New sets of features have been extracted from the original fish followed by the development of a two-level classifier to improve the generalization properties of the trained classifiers. The statistical features, such as mean, max, std, variance, were extracted from the Fishes data, a Part of the data set was used for training and the other part for testing of the proposed network. Evaluation carried out on 3 Fish species I (Tilapia), Fish II (Carpio) and Fish III(Tengra).

76

An Intelligent System for Fish Freshness Quality Assessment Using ANN

The use of commercial E-nose in fish industry and quality control such as assessment of Fish freshness is the subject of great interest. After the fish is caught, it starts degrading. Environmental conditions such as temperature and water contents play a significant role in maintaining the freshness of the Fish. E-nose can be employed not only to estimate the freshness but also it can be used to predict how fast it degrades in a given environmental condition. E-nose can be also employed to control the environmental conditions via a certain feedback mechanism to prolong fish freshness.

In this research work, we presented a fish freshness assessment method based on a portable E- nose and ANN classifiers. The array of six series sensors, forming the basis of the E-nose, responded to the signal pattern specific to the different days of each fish type. The ANN-based classifiers processed these signals and assigned the freshness level to the individual fish. The proposed method was tested on the samples of three fish over three/3 days. The results were obtained using similar architecture for all 3/three networks (100, 20, and 2 neurons in the input, hidden, and output layers, resp.). The networks were trained with different training data sets, collected from individual fish; therefore the weight values among their layers were different. After training the purpose of using three different networks was to increase the accuracy of the system. The quality assessment of fish freshness for individual fish was performed by a specific network which was trained for the species. The realized system is extremely quick, because a trained neural network arranges data in real time, the choice of using neural network ,among the mathematical model was motivated by the natural applications that this methodology finds in the freshness problems.

The common disadvantages with respect to quality control within industrial environment are that the process is slow and the analysis requires laboratory facilities

77

and qualified staff. Moreover, there is arising difficulty in establishing standards for use in various locations. The key obstacle in the way of this system being considered as a commercial solution lies in the fact that quality controllers/inspectors need to evaluate the freshness of a batch of fishes rather than individual sample. Employment of this system to process batch of fishes is still being explored. In conclusion, E-nose can be employed not only to estimate the freshness but also it can be used to predict how fast it degrades in a given environmental condition. E-nose can be also employed to control the environmental conditions via a certain feedback mechanism to prolong fish freshness. Using three different networks can increase the accuracy of the system. Further research is being undertaken to make the system commercially available.

6.2 Future Scope

This research is a preliminary work to store and analyzed the sensor data using ANN. The following are some of the identified issues for further research.

Significant testing must be done with more fish to show system and fish reproducibility. Fish freshness quality assessment with the series of sensors of array should incorporate a wider range of fish species and correlate with sensory panel analysis and with gas chromatography/mass spectrometry to classify and quantify the fish freshness.

The testing presented in this work evaluated from whole fish not small samples of fishes. A significant application for this technology is for food processors and distributors to analytically quantify the freshness of the fish samples therefore testing should be performed with whole fish.

78

Additional testing must be performed at fish processing plants and fish markets because there will be widely varying ambient conditions present when the system should be used. Most importantly, fish markets and auctions will have a significant background of fish odors due to amount of fish and entrails present. An important function of the sensor system is to sample the fish and indicate its freshness in the presence of possibly severely degraded samples.

79

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88

APPENDIX

APPENDIX A

TABLE -1 FISH A TRAINING DATA SET

Sensor MQ4	*Sensor MQ2*	*Sensor MQ8*	*Sensor MQ5*	*Sensor MQ135*
142	*152*	*154*	*112*	*103*
141	*151*	*151*	*115*	*103*
141	*151*	*153*	*116*	*103*
141	*151*	*153*	*111*	*103*
142	*152*	*153*	*108*	*103*
142	*151*	*151*	*112*	*103*
141	*152*	*151*	*116*	*103*
141	*152*	*153*	*114*	*103*
141	*151*	*153*	*112*	*103*
142	*151*	*153*	*111*	*103*
141	*151*	*153*	*113*	*103*
141	*152*	*153*	*111*	*103*
141	*152*	*153*	*109*	*103*
141	*151*	*153*	*110*	*103*
141	*151*	*153*	*112*	*103*
141	*151*	*153*	*116*	*103*
141	*151*	*153*	*114*	*103*
142	*151*	*153*	*113*	*103*
141	*151*	*153*	*112*	*106*
141	*151*	*153*	*113*	*103*
141	*154*	*153*	*111*	*102*
141	*151*	*153*	*108*	*103*
141	*151*	*153*	*112*	*103*
141	*151*	*153*	*116*	*103*
141	*151*	*152*	*115*	*103*

141	***155***	***153***	***112***	***103***

89

141	*151*	*153*	*115*	*102*
141	*151*	*153*	*116*	*103*
141	*151*	*153*	*114*	*102*
141	*151*	*153*	*107*	*103*
141	*151*	*154*	*110*	*103*
141	*151*	*153*	*113*	*101*
138	*151*	*152*	*111*	*103*
141	*154*	*153*	*111*	*103*
141	*151*	*152*	*114*	*102*
140	*151*	*153*	*116*	*103*
142	*151*	*153*	*116*	*103*
144	*151*	*153*	*113*	*103*
141	*151*	*153*	*113*	*103*
141	*150*	*154*	*111*	*103*
140	*151*	*153*	*111*	*98*
139	*151*	*152*	*110*	*104*
140	*151*	*152*	*108*	*104*
141	*151*	*153*	*111*	*104*
141	*151*	*153*	*111*	*104*
141	*155*	*153*	*112*	*105*
141	*151*	*151*	*110*	*105*
141	*149*	*153*	*115*	*105*
145	*151*	*153*	*116*	*105*
141	*151*	*153*	*115*	*105*

90

APPENDIX B

TABLE-2 FISH B TRAINING DATA SET

141	*151*	*153*	*110*	*103*
141	*151*	*152*	*113*	*104*
140	*150*	*152*	*112*	*104*
141	*150*	*150*	*114*	*103*
141	*151*	*153*	*113*	*103*
140	*149*	*153*	*116*	*103*
141	*150*	*154*	*116*	*102*
142	*150*	*153*	*114*	*103*
140	*151*	*152*	*109*	*103*
140	*150*	*150*	*112*	*103*
141	*150*	*152*	*111*	*103*
140	*150*	*152*	*108*	*103*
141	*150*	*152*	*108*	*104*
140	*151*	*152*	*112*	*103*
140	*149*	*152*	*117*	*103*
140	*151*	*152*	*115*	*105*
141	*151*	*152*	*113*	*103*
141	*150*	*152*	*115*	*103*
140	*151*	*152*	*116*	*101*
140	*150*	*152*	*114*	*103*
197	*451*	*465*	*186*	*261*
205	*452*	*465*	*190*	*267*
203	*462*	*478*	*186*	*273*
204	*462*	*478*	*189*	*276*
208	*463*	*478*	*189*	*274*
205	*461*	*476*	*187*	*271*
203	*460*	*476*	*190*	*270*
204	*461*	*475*	*189*	*271*
206	*460*	*476*	*191*	*273*
204	*443*	*458*	*196*	*263*
205	*444*	*458*	*196*	*263*
202	*441*	*455*	*195*	*261*
203	*440*	*455*	*195*	*261*
201	*439*	*454*	*194*	*260*
199	*454*	*468*	*186*	*263*
196	*445*	*458*	*184*	*257*

195	*444*	*458*	*186*	*258*

91

194	*442*	*458*	*186*	*260*
195	*443*	*456*	*187*	*257*
191	*439*	*453*	*183*	*254*
191	*439*	*453*	*183*	*253*
775	*592*	*828*	*637*	*527*
775	*592*	*828*	*637*	*527*
775	*592*	*829*	*638*	*527*
775	*592*	*828*	*637*	*526*
775	*591*	*828*	*637*	*526*
775	*591*	*828*	*638*	*526*
775	*591*	*828*	*638*	*526*
774	*591*	*828*	*637*	*525*
773	*591*	*829*	*637*	*525*

92

APPENDIX C

TABLE-3 FISH C TRAINING DATA SET

206	436	466	199	273
204	433	456	192	272
205	437	467	194	272
207	445	469	196	280
212	439	472	202	275
203	437	465	191	274
201	439	465	194	274
201	432	468	193	276
205	441	466	196	280
204	439	471	195	281
209	440	468	187	281
203	441	466	194	280
192	436	469	185	283
208	442	470	187	277
207	440	465	190	275
207	443	468	194	280
208	439	464	196	276
207	445	466	196	280
203	439	471	197	282
206	444	467	195	279
202	440	471	198	283
204	442	467	197	278
204	438	469	198	278
210	440	471	200	285
209	437	474	190	278
205	439	470	196	282
205	438	469	187	278
202	440	470	194	279
199	439	469	190	281
200	445	470	188	275
200	442	472	183	278
199	448	469	189	285
210	442	471	187	278
207	441	473	195	285
216	451	480	199	284
209	446	474	192	281

204	*444*	*474*	*191*	*281*

93

202	*443*	*473*	*191*	*280*
202	*443*	*473*	*188*	*279*
202	*443*	*472*	*188*	*278*
202	*444*	*473*	*190*	*280*
202	*444*	*474*	*189*	*279*
200	*444*	*474*	*191*	*282*
205	*448*	*476*	*192*	*281*
203	*446*	*475*	*191*	*281*
203	*446*	*475*	*191*	*281*
203	*445*	*475*	*191*	*281*
202	*445*	*475*	*190*	*280*
202	*445*	*474*	*190*	*280*
203	*446*	*475*	*190*	*281*
203	*446*	*476*	*191*	*281*