

**DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED
SCIENCES**

**FISH FRESHNESS DETECTION BY DIGITAL
IMAGE PROCESSING**

**by
Aydoğan KARAGÖZ**

**January, 2013
İZMİR**

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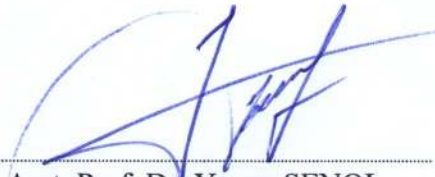
**A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfilment of the Requirements for the Degree of Master of
Science in Electrical and Electronics Engineering**

**by
Aydoğan KARAGÖZ**

**January, 2013
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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **“FISH FRESHNESS DETECTION BY DIGITAL IMAGE PROCESSING”** completed by **AYDOĞAN KARAGÖZ** under supervision of **ASST. PROF. DR. YAVUZ ŞENOL** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.



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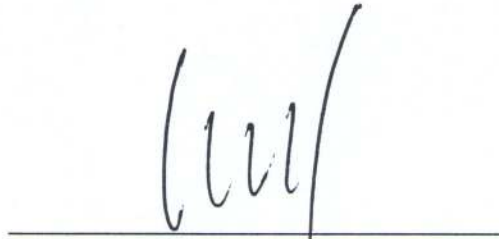
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Aydoğın KARAGÖZ

FISH FRESHNESS DETECTION BY DIGITAL IMAGE PROCESSING

ABSTRACT

Fish is a great food to consume. It is healthy, delicious, but has very limited shelf life. After that limited time, consuming the fish can damage people's health. Fish also start involving safety aspects such as being free from harmful bacteria, parasites or chemicals.

In order to decide whether a fish is fresh or not, there are some tips like checking it's eyes, smell or gills. All of these methods require experience, detailed knowledge about fish and give results that are changing from person to person.

In this thesis, a practical way of determining the freshness of fish is proposed. Photographs of fish are taken by mobile phone's camera and no extra sensors are used. Images are processed using MATLAB and some informative features are extracted. With the use of those features, an artificial neural network decides the freshness of the fish.

With the proposed technique, four different features are obtained to determine the freshness of the fish, three of which are related with the shape and the other is related to the colour. By using the features obtained from the shape, 90% of the test fish have been correctly recognized. With the addition of the colour feature all the test fish have been successfully classified. These results prove that the proposed technique can be easily and successfully used to detect the freshness of the fish.

Keywords: Image processing, fish freshness, artificial neural networks

SAYISAL GÖRÜNTÜ İŞLEME İLE BALIK TAZELİĞİNİN BELİRLENMESİ

ÖZ

Balık iyi bir besindir. Sağlıklı ve lezzetli olmasına rağmen raf ömrü çok sınırlıdır. Bu raf ömründen sonra balık tüketilmesi insan sağlığına zarar verebilir. Balık aynı zamanda zararlı bakteriler, parazitler veya kimyasallar içermeye de başlar.

Balık tazeliğini anlamak için; gözlerini, kokusunu ya da solungaçlarını incelemek gibi bazı basit yöntemler bulunmaktadır. Ancak, bu yöntemler tecrübe ve balık konusunda ayrıntılı bilgi gerektirdiği gibi kişiden kişiye değişen öznel bir sonuç verir.

Bu tezde balık tazeliğini belirlemeye yarayan pratik bir yöntem sunuldu. Balık görüntülerini elde etmek için bir cep telefonunun kamera özelliği kullanıldı ve başka bir sensör kullanılmadı. Görüntüler MATLAB kullanılarak işlendi ve bazı bilgi verici özellikler elde edildi. Bu bilgi verici özellikler ile yapay sinir ağları eğitildi ve balık tazeliği belirlendi.

Önerilen yöntemde, üç tanesi balığın şekli ve diğeri balığın rengiyle ilgili dört farklı bilgi çıkartıldı. Sadece şekil ile ilgili bilgilerle, test balıklarının %90'ı başarılı bir şekilde tanımlandı. Renk bilgisinin de eklenmesiyle, bütün balıklar başarılı bir şekilde tanımlandı. Bu sonuçlar sunulan yöntemin kolay ve başarılı bir şekilde balık tazeliğine karar vermek amacıyla kullanılabileceğini ispatlar.

Anahtar sözcükler: Görüntü işleme, balık tazeliği, yapay sinir ağları

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

Fish is a high-protein, low-fat food that provides a range of health benefits. White-fleshed fish, in particular, is lower in fat than any other source of animal protein, and oily fish are high in omega-3 fatty acids, or the “good” fats. Since the human body can’t make significant amounts of these essential nutrients, fish are an important part of the diet. Also, fish are low in the “bad” fats commonly found in red meat, called omega-6 fatty acids.

Fish is a great food, but it has a very limited shelf life. If some fish is not going to be frozen, it had better been consumed in the next 24 hours. Eating fish after that time can cause food poisoning or other similar conditions.

If a market cannot sell all their fish in that day, selling the same fish on following days can damage people’s health. It may also involve safety aspects such as being free from harmful bacteria, parasites or chemicals. It is important to remember that "quality" implies different things to different people and is a term which must be defined in association with an individual product type.

It is important to determine the fish freshness for the buyer in daily life. Normally, there is no practical way of making this decision for the benefit of the buyer. So far, almost all of the proposed methods to detect fish freshness required laboratory environments.

In this thesis, a practical and non-invasive way of deciding freshness of a fish, using Digital Image Processing is proposed. Fish photographs are taken by a mobile phone’s camera and in this study, sardines was used since it is one of the most consumed locally available fish. In order to standardize photographs a mechanism was designed. Image Processing and Neural Network implementations have been developed using MATLAB

1.2 Outline

Chapter 1 presents an introduction to the project.

Chapter 2 presents general knowledge on deciding freshness of the fish and refers existing methods.

In Chapter 3 Digital Image Processing techniques, Point Operations, Neighbourhood Operations, Morphological Operations and Colour Image Processing are explained briefly.

Chapter 4 gives some theoretical information about Artificial Neural Networks and explains Multilayer Perceptrons and Backpropagation Algorithm.

In Chapter 5, design details of the fish freshness system described from image acquisition to neural network output. Design is considered as 4 parts; image acquisition, pre-processing, feature extraction and fish freshness determination using neural networks.

In Chapter 6, conclusion and future works are presented.

CHAPTER TWO

FISH QUALITY ASSESSMENT

Freshness is one of the most important quality attributes for fish processing. It indicates the status of numerous physical, chemical, biochemical and microbiological changes in fish. Traditionally, freshness assessment has been based on organoleptic tests by humans, including evaluating the appearance of skin and eyes, testing the flesh firmness and elasticity, and smelling the odour shown on table 2.1 (Larsen *et al.* 1992). This method gives an immediate evaluation of quality and can be done without harming to the fish. However, human examinations are generally subjective, even for experienced and well-trained personnel (Jensen and Undeland, 1997). Furthermore, it is impossible for humans to make quantitative assessment and to take care of assessment results reliable among different assessors. Consequently, instrumental methods independent of the subjective opinion of human judges are needed to meet the requirement for quality measurement in the fish industry (Pons-Sanchez-Cascado *et al.*, 2006).

Several instrumental methods have been recommended to assess the condition of fish freshness, such as detection of chemical changes associated with microbial growth in fishes (Dainty, 1996), amperometric biosensors for determination of amines (Niculescu *et al.*, 2000), platinum electrodes to detect hydrogen peroxide (Volpe and Mascini, 1996), enzyme reactors-based systems (Carsol and Mascini, 1998), and spectrofluorimeter for the monitoring of fish freshness based on front-face fluorescence spectroscopy (Dufour *et al.*, 2003). Color imaging was used for assessing fish freshness based on the color of fish muscle with respect to the identified regions of interest. These regions of interest are then processed to produce an R(Red) G(Green) B(Blue) color index (Yasin, 2008). However, it is not easy to establish the relationship between color measurement and the degree of fish freshness. A fish freshness meter was developed to identify fish freshness according to the dielectric properties of the fish skin and muscle (Azeri *et al.*, 2009), and an electronic tongue using a thick-film array of electrodes was developed for fish freshness analysis (Gil *et al.*, 2008).

Table 2.1 Quality assessment scheme used to identify the quality index demerit score

Quality parameter	Character	Score
General appearance	Skin	0, Bright shining 1, Bright 2, Dull
	Bloodspot on gill cover	0, None 1, Small, 10-30% 2 Big, 30-50% 3 Very big, 50-100%
	Stiffness	0, Stiff, in rigor mortis 1, Elastic 2, Firm 3, Soft
	Belly	0, Firm 1, Soft 2, Belly burst
	Smell	0, Fresh 1, Neutral 2, Musty/sour 3, Stale meat/rancid
Eyes	Clarity	0, Clear 1, Cloudy
	Shape	0, Normal 1, Plain 2, Sunken
Gills	Colour	0, Characteristic, red 1, Faded, discoloured
	Smell	0, Fresh 1, Sour
Sum of scores		(min. 0 and max. 30)

Almost all of the proposed methods require laboratory environments, and none of them are practical for average person that has not specialized on the specific area. Currently available detection techniques are described in the following subsections.

2.1 A Novel Technique for Rapid Evaluation of Fish freshness Using Colorimetric Sensor Array

In that study, Huang X. et al developed an olfaction system based on colorimetric sensor array for fish freshness evaluation (Huang X. et al 2010). Nine chemically responsive dyes were selected according to their sensitivity to volatile compounds typically occurring during spoilage in fish. Printing selected dyes on a reverse phase

silica gel plate made the colorimetric sensor array. Detection on fish of chub was made every 24 h within seven days. A colour change profile for each sample was obtained by differentiating the images of the sensor array before and after exposure to the odour of sample. The digital data representing the colour change profiles for the fish samples were analysed using principal component analysis. The fish samples were classified into three freshness groups using a radial basis function neural network, with an overall classification accuracy of 87.5%.

2.2 An Electronic Tongue for Fish Freshness Analysis Using a Thick-Film Array of Electrodes

Gil L. et al (2008) report on the development of an electronic tongue as potential tool for fish freshness determination. Their studies were carried out following the evolution with time on fillet of cultured sea bream. The electronic tongue consists of 16 potentiometric electrodes of the type metal, metal oxide and insoluble metal salts. Graphite was also used as electrode. Fish freshness indicators such as texture, pH, colour, microbial analysis, total volatile basic nitrogen and biogenic amines were also determined versus time. The affectivity of the electronic tongue in the assessment of the evolution with time of fish fillets was evaluated. First the electronic tongue was used to classify samples according to time. Perceptron and adaptive resonance theory were used to discriminate between the data from different days. In a second step, the electronic tongue was used to predict the results obtained from chemical and biochemical analyses by building quantitative partial least square (PLS) models. A remarkable correlation was found between the electronic tongue formed by the 16 simple electrodes and parameters such as total biogenic amines, pH, TVB-N and microbial analysis with correlation coefficients larger than 0.98.

2.3 A Practical Approach For Fish Freshness Determinations Using a Portable Electronic Nose

O'Connel M. et al (2001) developed an electronic nose and applied to fish freshness determinations of Argentinean hake. The applied methodology differs from

the typical ones based on the headspace method or glass syringe manipulation. In this study, a weighted piece of fish is introduced into a sensor's chamber and the signals of the sensors due to the fish emissions are recorded as function of time. Commercial gas sensors, based on tin dioxide, were used. Analysis of the individual sensor signals and of the array's pattern was performed. An increase of the signals was observed with increasing storage days and the mass of the hake pieces (up to 50 g). The obtained response patterns are independent of the weight but change after some days of storing, indicating the rottenness of the sample. Two different patterns are obtained, associated to rotten and non-rotten samples, respectively. These patterns are independent of storage conditions; for example, the pattern of a rotten sample is the same, if the piece was stored several days in a refrigerator or if it was kept out for 1 day. Hence, it is quick and easy to identify between fresh and old samples. These results were confirmed by performing principal component analysis (PCA).

CHAPTER THREE

IMAGE PROCESSING

Digital image processing is the use of computers to manipulate digital images. Digital image processing has two principal aims: enhancement of image for humans; and processing of image data for autonomous machine perception, for storage, transmission, and representation (Gonzalez, 2002).

3.1 Point Operations

Point processing is the most fundamental method of image processing. This technique creates a pixel value in the target image, which is determined only by the value of the corresponding pixel in the input image. This can be explained by the *mapping function*

$$s = M(r) \quad (3 - 1)$$

where r and s are the pixel values in the original and target images, correspondingly. The mapping function M determines the effect on the output image. With the use of mapping function basic operations like thresholding, gamma correction as well as histogram equalization can be accomplished.

3.2 Neighbourhood Operations

Neighbourhood operations use small region or neighbourhood of pixels to generate the resulting pixel. The most famous neighbourhood operator is convolution. To convolve something means to coil together. In digital image processing, convolving is used to achieve some desired result from local area of pixels. Sampling is as important as convolution. Different methods for sampling help this to occur. There are many different applications of neighbourhood operators, ranging from digital filters to sharpening, warping and transforming images.

When implementing the point operations, it is possible to perform a given function and, if desired, save the resulting pixels in the same memory buffer, thereby destroying the original input pixels. For point operations this is not a problem,

because once an input pixel has been created its original value is no longer needed. This is not possible with neighbourhood operators because, even after an output pixel has been created, the matching input pixel at that position is contained in other neighbourhoods. Thus no input pixels can be overwritten until all related output pixels have been calculated.

While point operation algorithms generally requires two nested loops (one for the horizontal dimension and one for the vertical), neighbourhood operation programs usually requires four nested loops - two for the horizontal and vertical processing of the image, and two for the horizontal and vertical processing of the neighbourhood.

3.2.1 Convolution

One of the most famous techniques in all of image processing is convolution. It takes many forms and can be used to perform many operations. The general convolution equation, shown below is computationally expensive.

$$y[m,n] = x[m,n] * h[m,n] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} x[i,j] \cdot h[m-i,n-j] \quad (3-2)$$

This same operation can be shown in a pictorial form follows.

At the heart of this operation is the convolution mask or kernel, shown as M in these figures, which has individual mask elements, labelled M_{ij} . It is an array of numbers that has, just like a digital image, a horizontal and vertical dimension, with size usually denoted as $m \times n$. Each element in the mask is multiplied by the related pixel value in the neighbourhood of the input image, P, that has elements P_i, P_j . The results of all the multiplications are added together, and this summation is divided by the summation of the mask values. This denominator is known as the weight of the mask. The result of the division is a pixel, C_i, C_j , in the convolved image, C.

Convolution requires a lot of computational power. To calculate a pixel for a given mask of size $m \times n$, $m \cdot n$ multiplications, $m \cdot n - 1$ additions, and one division are required

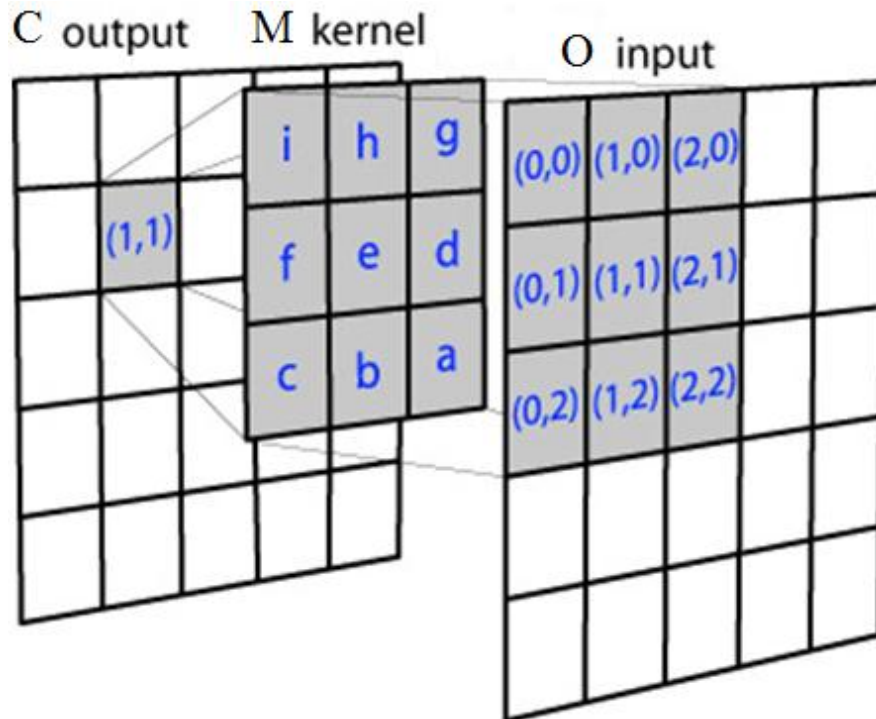


Figure 3.1 Convolution in pictorial form

So to perform a 3×3 convolution on a 1024×1024 colour image (a minimal convolution on an average-size image), 27 million multiplications, 24 million additions, and 3 million divisions are performed. For more substantial convolutions, such as 5×5 or 8×8 , on larger images the amount of computation required becomes very large indeed.

3.3 Morphological Operations

Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image. These techniques can be extended to grayscale images.

3.3.1 Basic concepts

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. According to [Wikipedia](#),

morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grayscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test.

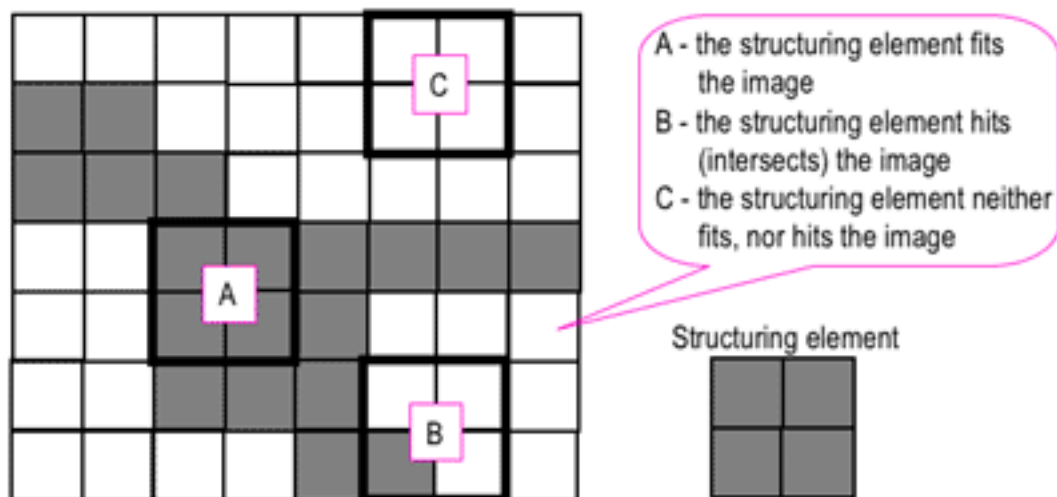


Figure 3.2 Probing of an image with a structuring element

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image.

The structuring element is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one:

- The matrix dimensions specify the size of the structuring element.
- The pattern of ones and zeros specifies the shape of the structuring element.

- An origin of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element. Various structuring elements are seen on Figure 3.3.

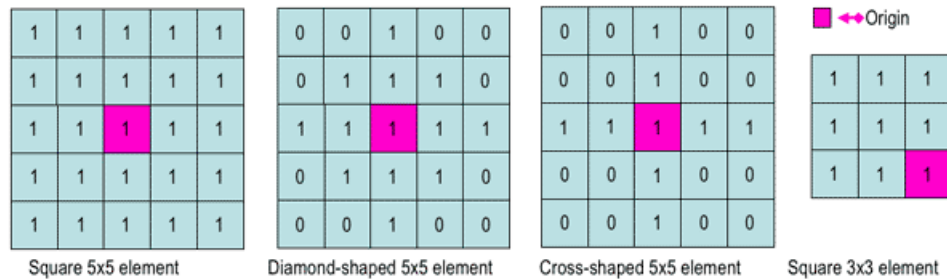


Figure 3.3 Examples of simple structuring elements.

A common practice is to have odd dimensions of the structuring matrix and the origin defined as the centre of the matrix. Structuring elements play in morphological image processing the same role as convolution kernels in linear image filtering.

When a structuring element is placed in a binary image, each of its pixels is associated with the corresponding pixel of the neighbourhood under the structuring element as seen on Figure 3.4. The structuring element is said to fit the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to hit, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1.



Figure 3.4 Fitting and hitting of a binary image with structuring elements s_1 and s_2 .

Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

3.3.2 Fundamental operations

More formal descriptions and examples of how basic morphological operations work are given in the Hypermedia Image Processing Reference ([HIPR](#)) developed by Dr. R. Fisher et al. at the Department of Artificial Intelligence in the University of Edinburgh, Scotland, UK.

3.3.2.1 Erosion and Dilation

The **erosion** of a binary image f by a structuring element s (denoted $f \ominus s$) produces a new binary image $g = f \ominus s$ with ones in all locations (x,y) of a structuring element's origin at which that structuring element s fits the input image f , i.e. $g(x,y) = 1$ if s fits f and 0 otherwise, repeating for all pixel coordinates (x,y) .



Figure 3.5 Greyscale image



Figure 3.6 Binary image by thresholding



Figure 3.7 Erosion: a 2×2 square structuring element

Erosion with small (e.g. 2×2 - 5×5) square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions as seen on Figures 3.5 to 3.7. The holes and gaps between different regions become larger, and small details are eliminated. Erosion with dilation is one of the most used morphological operations in digital image processing. The structuring element is the most important part in the morphological operations. Example application: Assume we have received a fax of a dark photocopy. Everything looks like it was written with a pen that is bleeding. Erosion process will allow thicker lines to get skinny and detect the hole inside the letter "o". Easiest way to describe it is to imagine the same text is written with a thinner pen.

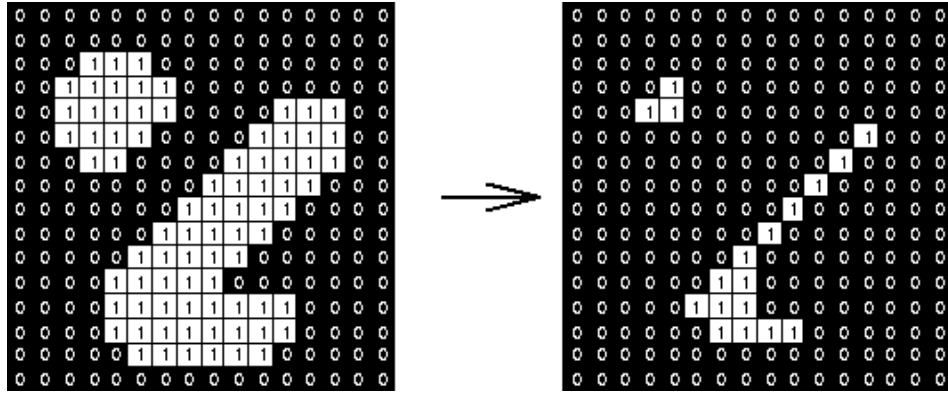


Figure 3.8 Erosion: a 3×3 square structuring element

Larger structuring elements have a more pronounced effect, the result of erosion with a large structuring element being similar to the result obtained by iterated erosion using a smaller structuring element of the same shape as seen on Figure 3.8. If s_1 and s_2 are a pair of structuring elements identical in shape, with s_2 twice the size of s_1 , then

$$f \ominus s_2 \approx (f \ominus s_1) \ominus s_1 \quad (3 - 3)$$

Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest, too. By subtracting the eroded image from the original image, boundaries of each region can be found:

$$b = f - (f \ominus s) \quad (3 - 4)$$

Where f is an image of the regions, s is a 3×3-structuring element, and b is an image of the region boundaries.

The dilation of an image f by a structuring element s (denoted $f \oplus s$) produces a new binary image

$$g = f \oplus s \quad (3 - 5)$$

with ones in all locations (x,y) of a structuring element's origin at which that structuring element s hits the the input image f , i.e. $g(x,y) = 1$ if s hits f and 0 otherwise, repeating for all pixel coordinates (x,y) . Dilation has the opposite effect to erosion -- it adds a layer of pixels to both the inner and outer boundaries of regions.

The holes enclosed by a single region and gaps between different regions become smaller, and small intrusions into boundaries of a region are filled in:



Figure 3.9 Binary image



Figure 3.10 Dilation with a 2x2 square structuring element

Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are *dual* operations in that they have opposite effects. Let f^c denote the complement of an image f , i.e., the image produced by replacing 1 with 0 and vice versa. Formally, the duality is written as

$$f \oplus s = f^c \ominus s_{rot} \quad (3 - 6)$$

where s_{rot} is the structuring element s rotated by 180° . If a structuring element is symmetrical with respect to rotation, then s_{rot} does not differ from s . If a binary image is considered to be a collection of connected regions of pixels set to 1 on a background of pixels set to 0, then erosion is the fitting of a structuring element to these regions and dilation is the fitting of a structuring element (rotated if necessary) into the background, followed by inversion of the result.

3.4 Colour Image Processing

The human visual system can distinguish hundreds of thousands of different colour shades and intensities, but only around 100 shades of grey. Therefore, in an image, a great deal of extra information may be contained in the colour, and this extra information can then be used to simplify image analysis, e.g. object identification and extraction based on colour.

Experimental evidence shows that color can be divided into three principal sensing categories corresponding to roughly red, green, and blue: (%65 of cones are sensitive to RED, 33% to GREEN and 2% to blue)

Three independent quantities are used to describe any particular colour. The *hue* is determined by the dominant wavelength. Visible colours occur between about 400nm (violet) and 700nm (red) on the electromagnetic spectrum, as shown in Figure 3.11.

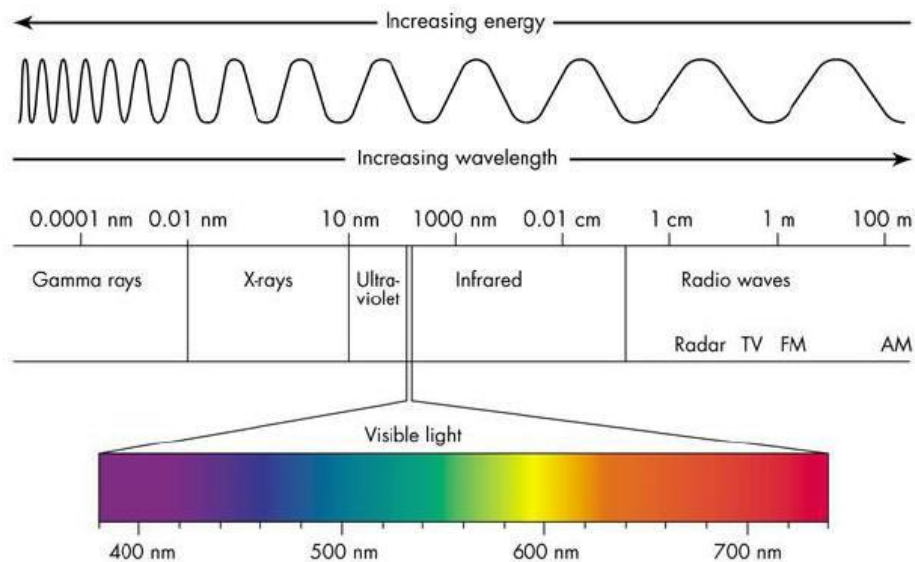


Figure 3.11 The visible spectrum

The *saturation* is determined by the excitation purity, and depends on the amount of white light mixed with the hue. A pure hue is fully saturated, i.e. no white light mixed in. Hue and saturation together determine the *chromaticity* for a given colour. Finally, the *intensity* is determined by the actual amount of light, with lighter corresponding to more intense colours.

Achromatic light has no colour - its only attribute is quantity or intensity. Grey level is a measure of intensity. The *intensity* is determined by the energy, and is therefore a physical quantity. On the other hand, *brightness* or *luminance* is determined by the perception of the colour, and is therefore psychological. Given equally intense blue and green, the blue is perceived as much darker than the green. Note also that our perception of intensity is nonlinear, with changes of normalized intensity from 0.1 to 0.11 and from 0.5 to 0.55 being perceived as equal changes in brightness.

Colour depends primarily on the reflectance properties of an object. We see those rays that are reflected, while others are absorbed. However, we also must consider the colour of the light source, and the nature of human visual system. For example, an object that reflects both red and green will appear green when there is green but no red light illuminating it, and conversely it will appear red in the absence of green light. In pure white light, it will appear yellow (= red + green).

3.4.1 The HSV Model

HSV (Hue, Saturation and Value) – defines a type of colour space. It is similar to the HSI model. The HSV colour space has three elements: hue, saturation and value. ‘Value’ is sometimes substituted with ‘brightness’ and then it is known as HSB. HSV is also known as the hex-cone colour model. The HSV colour space is shown in Figure 3.13.

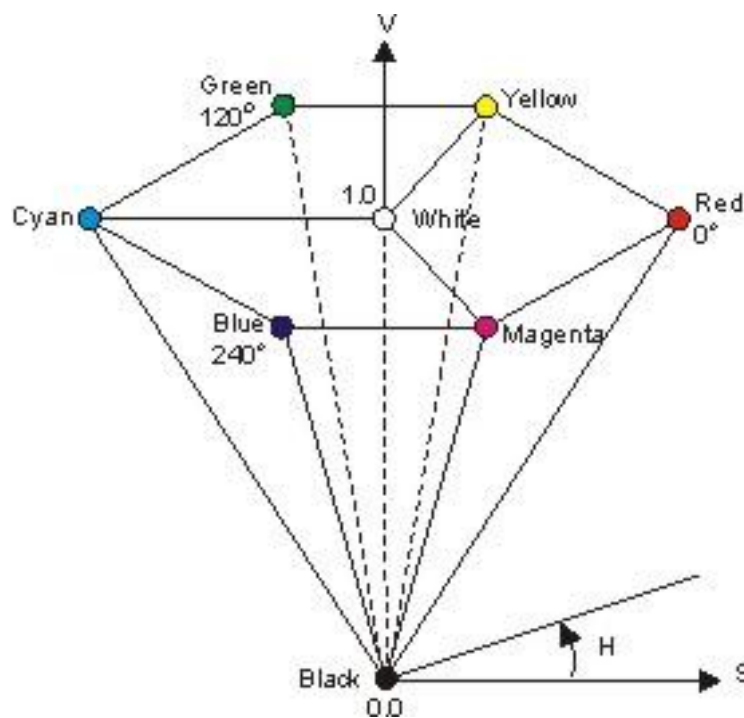


Figure 3.13 The HSV color space

3.4.1.1 Hue

Hue is expressed as a number from 0 to 360 degrees representing hues of red (starts at 0), yellow (starts at 60), green (starts at 120), cyan (starts at 180), blue (starts at 240), and magenta (starts at 300).

3.4.1.2 Saturation

Saturation indicates the range of grey in the colour space. It ranges from 0 to 100%. Sometimes the value is calculated from 0 to 1. A faded colour is due to a lower saturation level, which means the colour contains more grey.

3.4.1.3 Value

Value is the brightness of the colour and varies with colour saturation. It ranges from 0 to 100%. When the value is '0' the colour space will be totally black. With the increase in the value, the colour space brightness up and shows various colours.

CHAPTER FOUR

ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

4.1 The Biological Model

Artificial neural networks born after McCulloch and Pitts introduced a set of simplified neurons in 1943. These neurons were represented as models of biological networks into conceptual components for circuits that could perform computational tasks. The biological model of neural can be seen on Figure 4.1. The basic model of the artificial neuron is founded upon the functionality of the biological neuron.

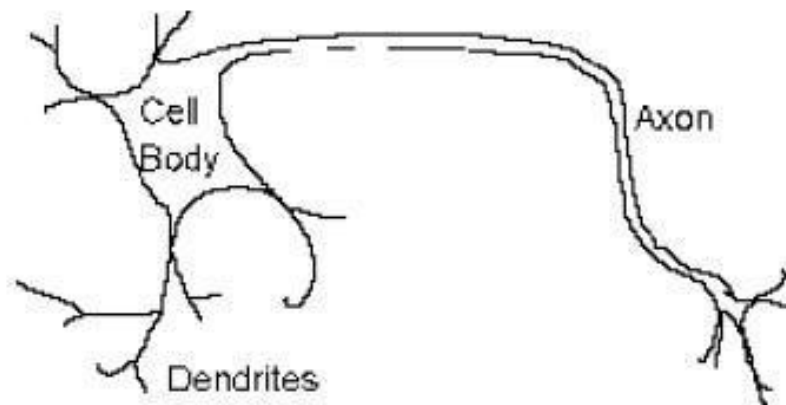


Figure 4.1 Biological neural network

4.2 The Perceptron

The perceptron is a program that learns **concepts**, i.e. it can learn to respond with *True* (1) or *False* (0) for inputs we present to it, by repeatedly "studying" examples presented to it.

The Perceptron is a single layer neural network whose weights and biases could be trained to produce a correct target vector when presented with the corresponding input vector. The training technique used is called *the perceptron learning rule*. The perceptron generated great interest due to its ability to **generalize** from its training vectors and work with randomly distributed connections. Perceptrons are especially suited for simple problems in pattern classification.

Perceptron network shown on Figure 4.2 consists of a single neuron connected to four inputs through a set of four weights.

The perceptron calculates its output using the following equation:

$$u * W > 0 \quad (4 - 1)$$

where u is the input vector presented to the network, W is the vector of weights.

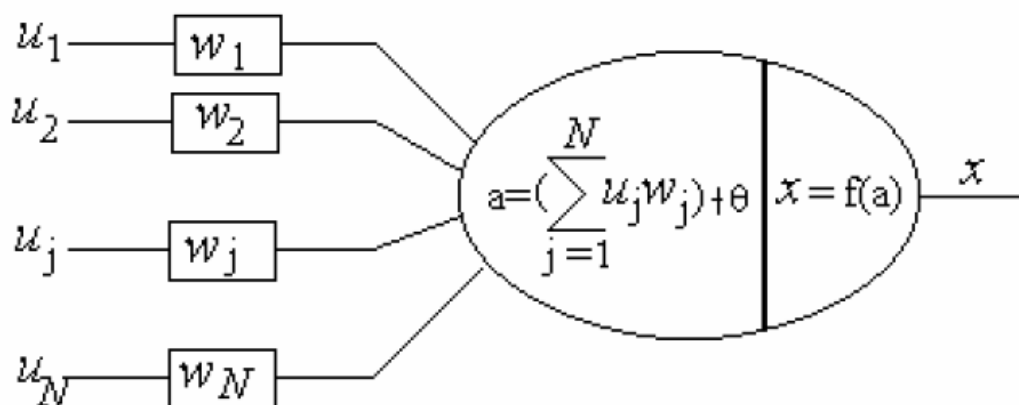


Figure 4.2 Artificial neuron model

4.3 Multilayer Perceptron Neural Networks

Network shown in Figure 4.3 has an input layer (on the left) with p neurons, one hidden layer (in the middle) with p neurons and an output layer (on the right) with m neurons. There is one neuron in the input layer for each predictor variable. In the case of categorical variables, $N-1$ neurons are used to represent the N categories of the variable.

Input Layer — A vector of predictor variable values ($x_1 \dots x_p$) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron.

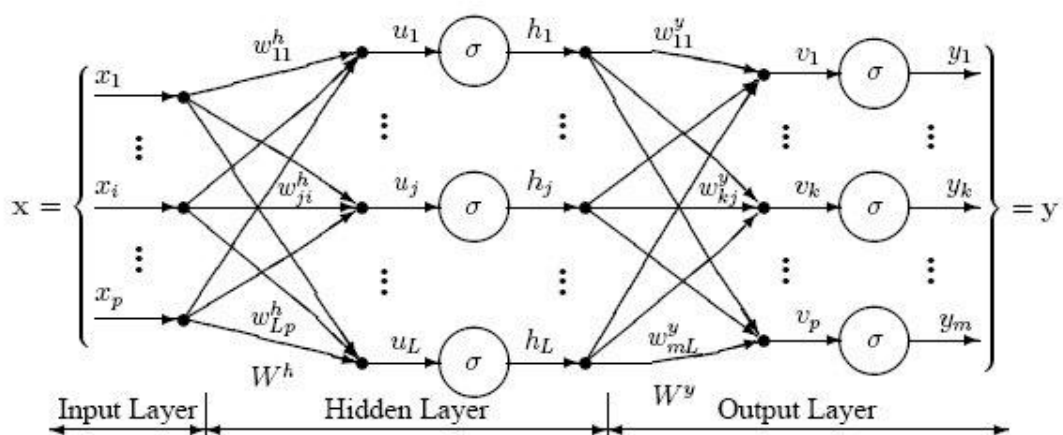


Figure 4.3 Multilayer perceptron neural network

Hidden Layer — Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (w_{ji}), and the resulting weighted values are added together producing a combined value u_j . The weighted sum (u_j) is fed into a transfer function, σ , which outputs a value h_j . The outputs from the hidden layer are distributed to the output layer.

Output Layer — Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (w_{kj}), and the resulting weighted values are added together producing a combined value v_j . The weighted sum (v_j) is fed into a transfer function, σ , which outputs a value y_k . The y values are the outputs of the network.

If a regression analysis is being performed with a continuous target variable, then there is a single neuron in the output layer, and it generates a single y value. For classification problems with categorical target variables, there are N neurons in the output layer producing N values, one for each of the N categories of the target variable.

4.3.1 Multilayer Perceptron Architecture

The network diagram shown above is a fully connected, three layer, feed-forward, perceptron neural network. “Fully connected” means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer. “Feed forward” means that the values only move from input to hidden to output layers; no values are fed back to earlier layers (a Recurrent Network allows values to be fed backward).

All neural networks have an input layer and an output layer, but the number of hidden layers may vary. Figure 4.4 shows a diagram of a perceptron network with one hidden layers and three total layers.

4.4 Backpropagation Training Algorithm

Backpropagation is a common method of training artificial neural networks so as to minimize the objective function. Arthur E. Bryson and Yu-Chi Ho described it as a multi-stage dynamic system optimization method in 1969. It was not until 1974 and later, when applied in the context of nural networks and through the work of Paul Werbos, David E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams that it

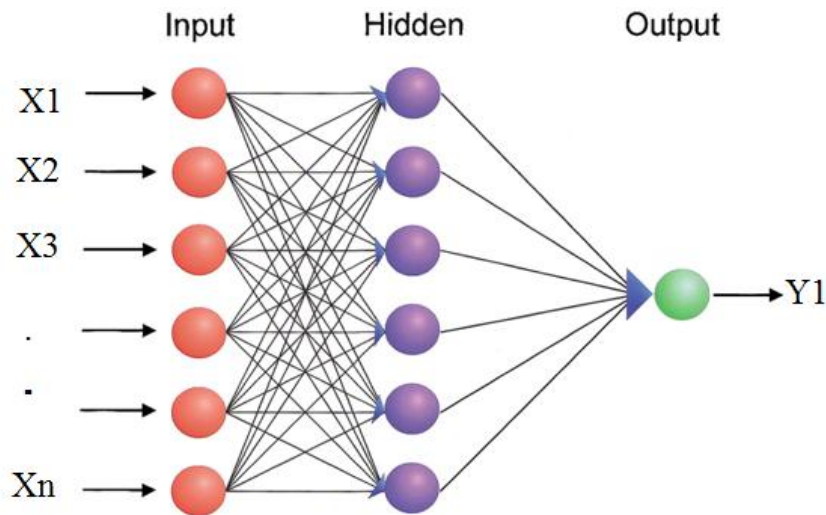


Figure 4.4 MLPNN with one hidden layer

gained recognition, and it led to a “renaissance” in the field of artificial neural network research.

It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). The term is an abbreviation for "backward propagation of errors". Backpropagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

4.4.1 Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Backward propagation of the propagation's output activations through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons.

4.4.2 Weight Update

For each weight-synapse follow the following steps:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Bring the weight in the opposite direction of the gradient by subtracting a ratio of it from the weight.

This ratio influences the speed and quality of learning; it is called the learning rate. The sign of the gradient of a weight indicates where the error is increasing; this is why the weight must be updated in the opposite direction.

Repeat Propagation and 2 Weight update the performance of the network is satisfactory.

CHAPTER FIVE

THE FISH FRESHNESS DETECTION SYSTEM DESIGN

In this chapter implementation of fish freshness detection system design is described in detail. The proposed fish freshness detection system consists of four parts as: image acquisition, pre-processing, feature extraction and artificial neural network based classification.

5.1 Image Acquisition

Image acquisition is the first stage of any vision system. After the image has been obtained, various methods of processing can be applied to the image to perform the many different vision tasks required today. However, if the image has not been acquired satisfactorily then the intended tasks may not be achievable, even with the aid of some form of image enhancement techniques.

5.1.1 Digital Cameras

Digital cameras have several advantages over analog cameras. Analog video is more susceptible to noise during data transmission than digital video. By digitizing the data at the camera level rather than at the image acquisition device, the signal-to-noise ratio is typically higher, resulting in better accuracy. Because digital cameras are not required to conform to television standards, they can offer larger image sizes and faster frame rates, as well as higher pixel resolutions. Digital cameras come with 10 to 16-bit grey levels of resolution as a standard for machine vision, astronomy, microscopy, and thermal imaging applications. Digital cameras use the same CCD type devices for acquiring images as analog; they simply digitize the video before sending it to the frame grabber.

5.1.2 Image Acquisition Setup

Fish photographs are taken by a mobile phone's camera. In order to standardize photographs a platform to hold both the fish and the camera has been constructed.

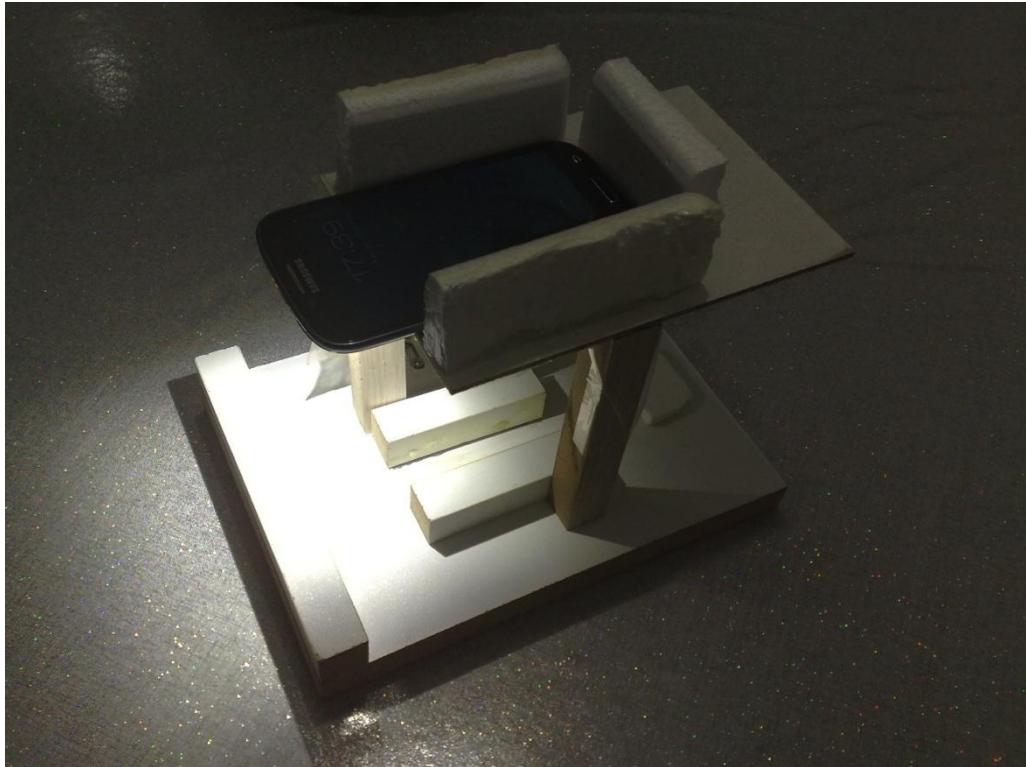


Figure 5.1 Image acquisition setup

The platform is made of wood and consists of two parts as base and the top part. As seen from the figure 5.1 fish is placed between two wooden sticks to provide stable and similar images. The camera is placed on the top part in a slot. In this set-up there is no additional lightning equipment to illuminate the fish. But the flashlight of the camera is enough for the application.

In this study, classification is based on fresh and stale fish and for this, photographs were taken at twelve hours time intervals. The first taken photographs represented the fresh fish and the last ones represented the stale fish. So, each fish feature has its one class and allows the application of supervised learning with neural networks.

All images are taken in colour mode and therefore to provide contrast between the fish and the setup base, the base was painted in red colour. In this study the camera resolution is set to 640x480 pixels, roughly occupying 500 kilobytes memory.

5.2 Pre-processing

Images taken from camera are containing too much data to be interpreted. Figure 5.2 shows the coloured image of a fish placed at the base of the platform. The image has to be pre-processed to obtain useful information. In this study, the following techniques were applied to collected images: grayscale conversion, binary gradient mask, dilation and removing redundant image parts. Example image is shown in figures 5.2 for fresh and stale fish.



Figure 5.2 Original image of a fresh fish

5.2.1 Grayscale Conversion

First of all image is needed to be converted into gray scale to obtain information about shape of the fish. In this way some image processing techniques can be easily applied. Moreover, dimension of the image can be reduced to one third of the actual image size. The Figure 5.3 shows the grayscale of the image.



Figure 5.3 Grayscale image

5.2.2 Binary Gradient Mask

As Figure 5.3 is examined it can be seen that there are lots of data in addition to fish image itself. This requires the elimination of the data, which is not related to the fish. In this way the fish can be detected. Another word process in detection is segmentation. Fish differs greatly in contrast from the background image. Operators, which calculate the gradient of an image in contrast, can detect changes. The gradient image can be calculated and a threshold can be applied to create a binary image containing the segmented edges of the fish. With the use of edge and the sobel operators a threshold value is calculated. Then threshold value is tuned and edge is used again to obtain an edge image that contains the segmented fish. The result of the edge detection can be seen in Figure 5.4.

Edge segmented image shows the borders of the fish and many distributed individual artifacts.

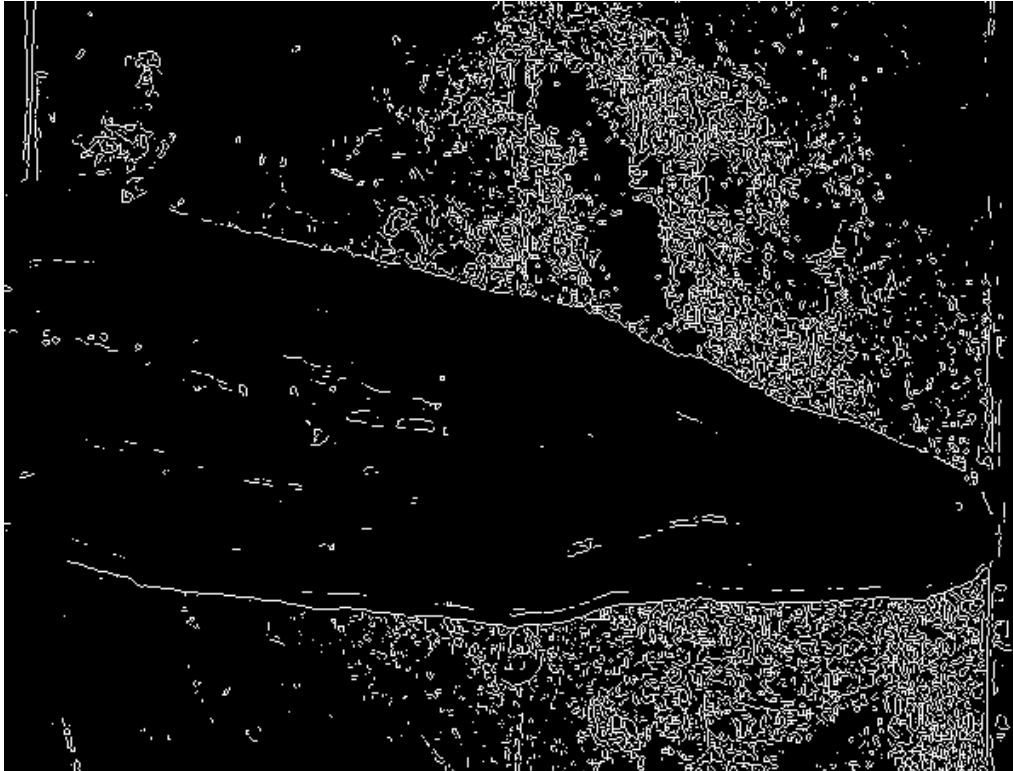


Figure 5.4 Binary gradient mask

5.2.3 Dilation

Edge segmented image shows high contrast points in the image. These points do

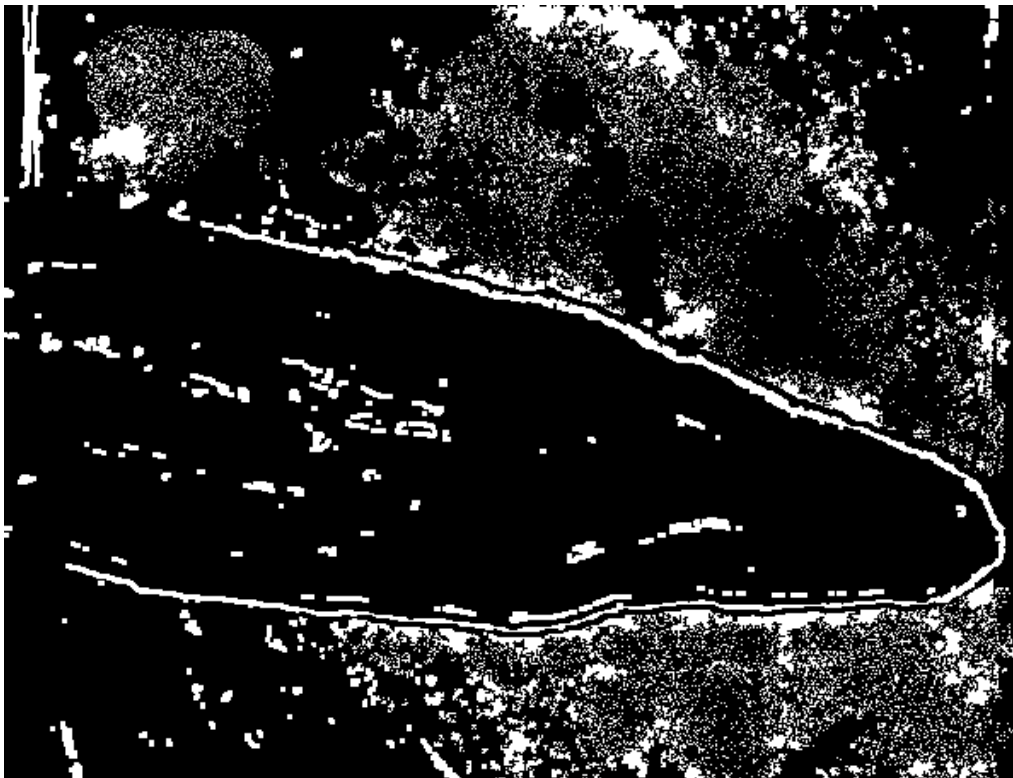


Figure 5.5 Dilated image

not quite describe the outline of the object of interest. Compared to the previous image, there are also other gaps and lines among the object. These gaps and lines can be eliminated by dilation using linear structuring elements, which can be created with the `strel` function.

The dilated image in figure 5.5 shows clear outline of the fish. However, further processing is required to remove unwanted data.

5.2.4 Removing Artefacts

The shape of the fish has been successfully segmented as shown in figure 5.5, but it is not the only object that has been found in the image. Any other objects other than the fish edges are needed to be removed. This requires the calculation of the sizes of all objects and choosing a threshold value for the biggest object. The object sizes are calculated using 8-connected neighbourhood connectivity rule. This rule was applied to all of the images and it was seen that a threshold value of 1500 is enough to obtain fish shape. Figure 5.6 shows binary fish image after application of the rule with the specified threshold value.

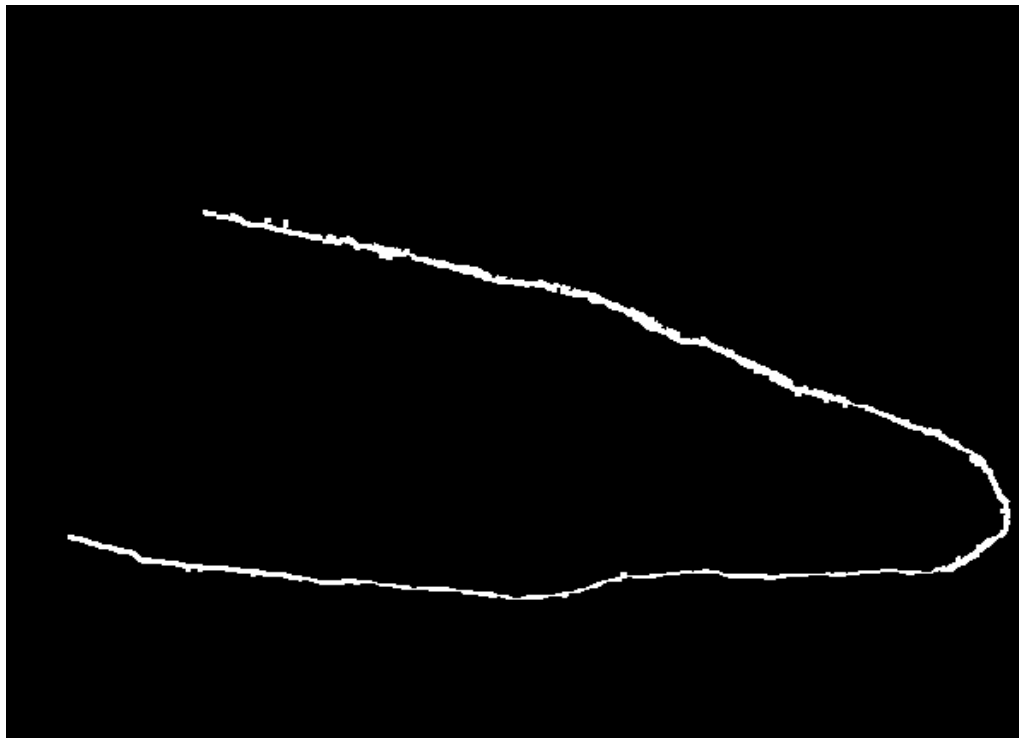


Figure 5.6 A fish image after removing unnecessary objects with eight connectivity

5.3 Feature Extraction

In order to classify the freshness of the fish as fresh and stale it is necessary to have some useful information obtained from the images.

After pre-processing steps, the black and white image is examined and contour of the fish is acquired by finding the distance between top and bottom white pixels. This method also eliminates the need for constant position of the fish.

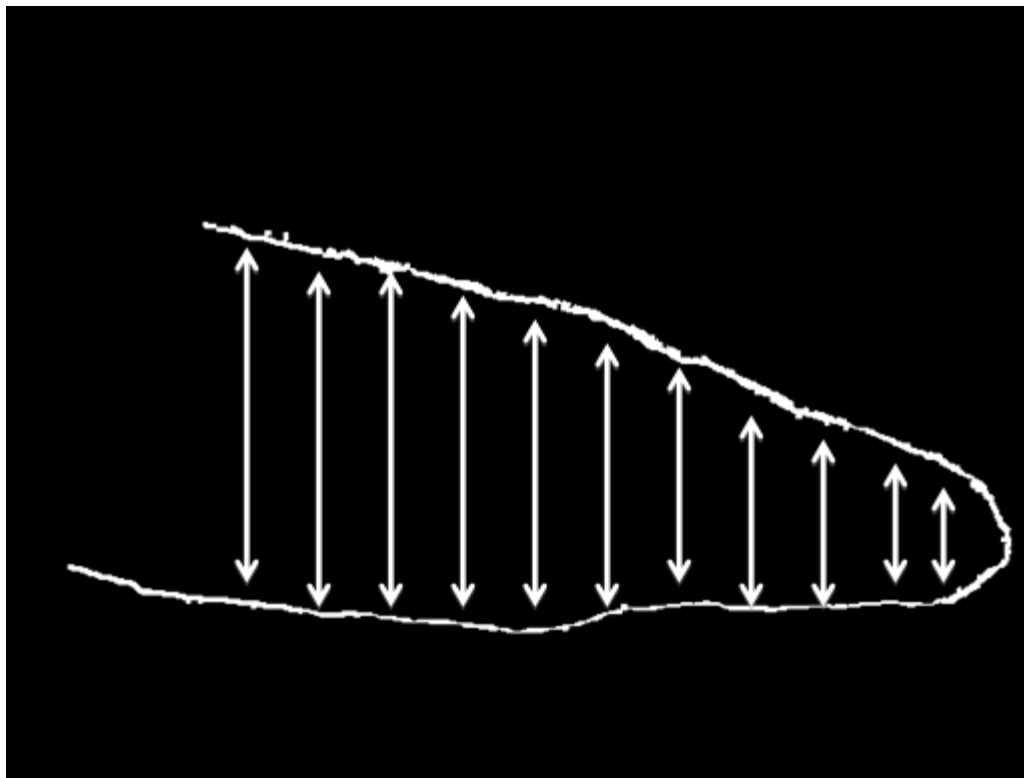


Figure 5.8 contour of the fish is acquired by finding the distance between top and bottom white pixels

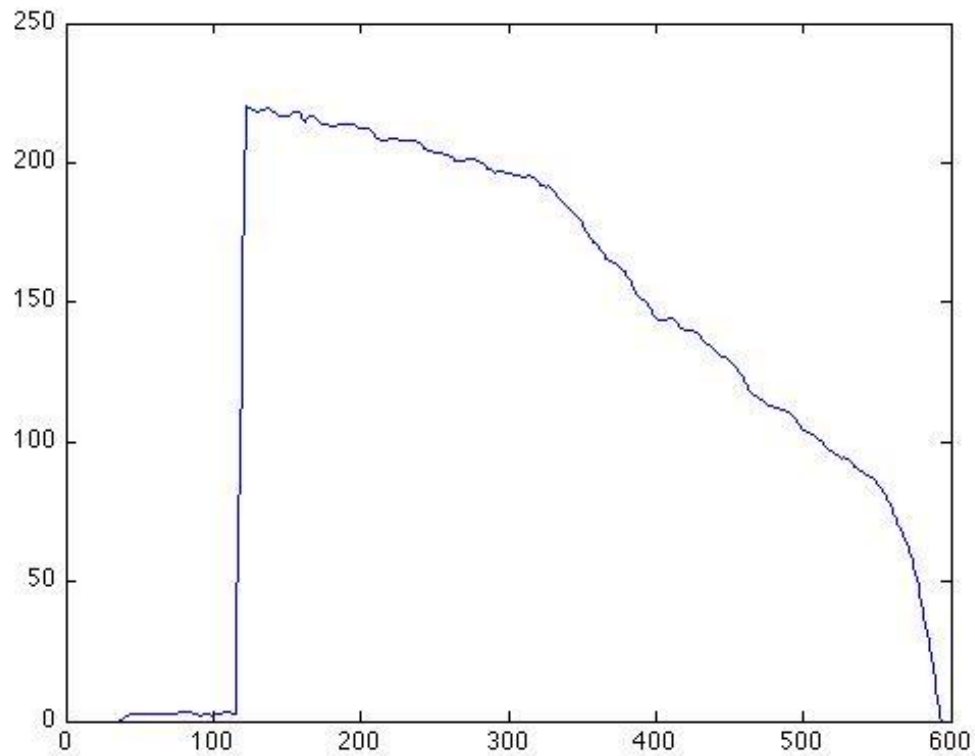


Figure 5.9 distance measure between two sides of the fish in perpendicular position.

Figure 5.9 shows the measured distance values. As seen the distance is zero at the end of the head and becomes bigger towards the body. When contours of the sample of fresh and stale fish are examined, it has been seen that general form of them differentiates substantially. In figure 5.10 the red coloured contours represents the fresh fish, whereas blue coloured contours represents stale fish. As seen from the figure there is no simple discrimination between the fresh and the stale fish. Therefore it is necessary to obtain additional features to simplify the classification.

When figure 5.10 is examined, there is no single trend from one end to other end, but there are different slopes in different subsections. To extract some distinguishing scalar values, contours are divided into five different regions (100 – 150, 150 – 200, 200 – 250, 250 – 300, 300 – 350) and their slopes can be calculated.

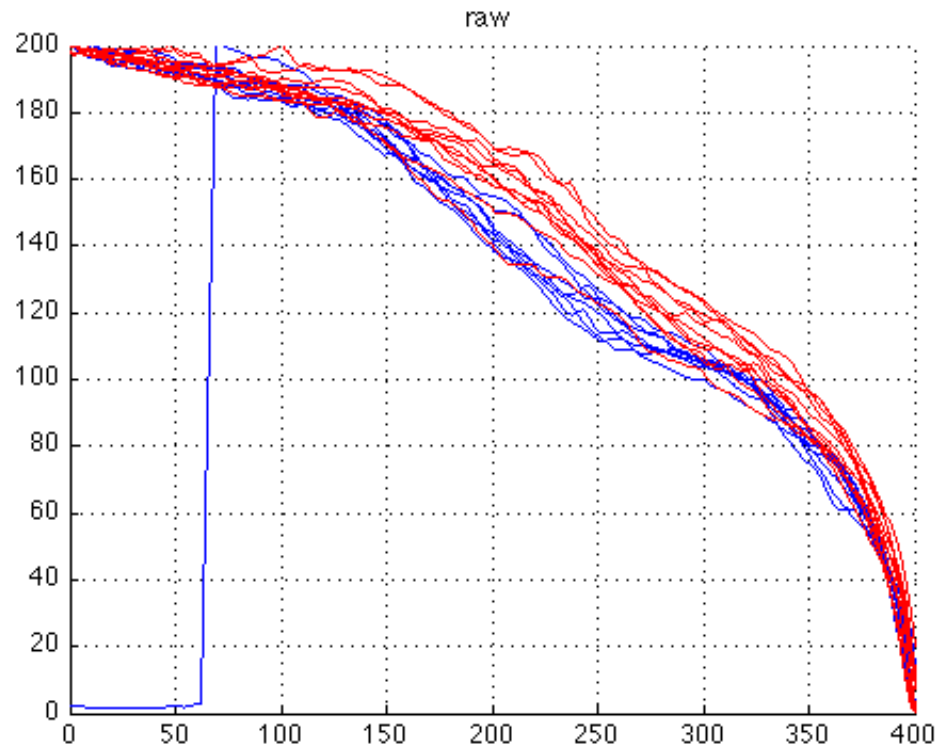


Figure 5.10 All the fresh and stale samples. Red colour represents fresh samples and blue colour represents stale samples.

Before calculating the slopes the contours are smoothed in order to eliminate high frequency changes. Each point is reshaped according to preceding and following three samples. Then, the slopes are calculated for ten fresh and ten stale fish according to the specified regions.

Table 5.1 gives the calculated slope values according to the regions.

	Regions				
Freshness	100 – 150	150 - 200	200 - 250	250 - 300	300 - 350
Stale 1	2,246	6,197	4,478	4,583	3,260
Stale 2	1,770	5,513	4,234	4,471	3,708
Stale 3	0,792	5,708	6,322	2,704	2,952
Stale 4	1,521	5,544	5,762	3,137	2,640
Stale 5	1,591	4,465	4,783	4,600	4,038
Stale 6	2,293	4,359	4,573	4,790	4,028
Stale 7	3,026	3,597	6,290	3,546	3,688
Stale 8	1,781	4,499	5,070	3,759	3,582
Stale 9	2,227	4,669	4,862	3,913	3,671
Stale 10	0,071	5,330	10,728	4,371	2,955
Fresh 1	1,557	2,114	4,047	5,761	4,280
Fresh 2	1,288	2,339	3,756	4,283	4,849
Fresh 3	0,735	4,233	4,099	5,359	4,105
Fresh 4	1,038	4,132	4,161	5,040	4,413
Fresh 5	1,348	2,005	4,747	6,881	4,612
Fresh 6	1,238	2,032	4,639	6,947	4,233
Fresh 7	0,350	2,965	3,812	6,462	4,523
Fresh 8	0,894	2,751	4,021	5,555	4,274
Fresh 9	2,451	4,005	3,704	3,670	4,077
Fresh 10	1,661	3,015	4,373	4,022	4,175
Test 1	2,293	4,644	4,573	4,790	4,028
Test 2	2,674	3,339	6,290	3,546	3,688
Test 3	2,040	4,842	5,070	3,759	3,582
Test 4	2,354	4,532	4,862	3,913	3,671
Test 5	0,928	4,990	10,728	4,371	2,955
Test 6	1,809	2,114	4,047	5,761	4,280
Test 7	1,544	2,339	3,756	4,283	4,849
Test 8	1,022	4,233	4,099	5,359	4,105
Test 9	0,752	4,132	4,161	5,040	4,413
Test 10	1,461	2,005	4,747	6,881	4,612

5.3.1 Feature 1

It has been observed that the area of the fish changes according to the freshness. When the fish is fresh, there is a larger area and the area becomes smaller when the fish becomes aged.

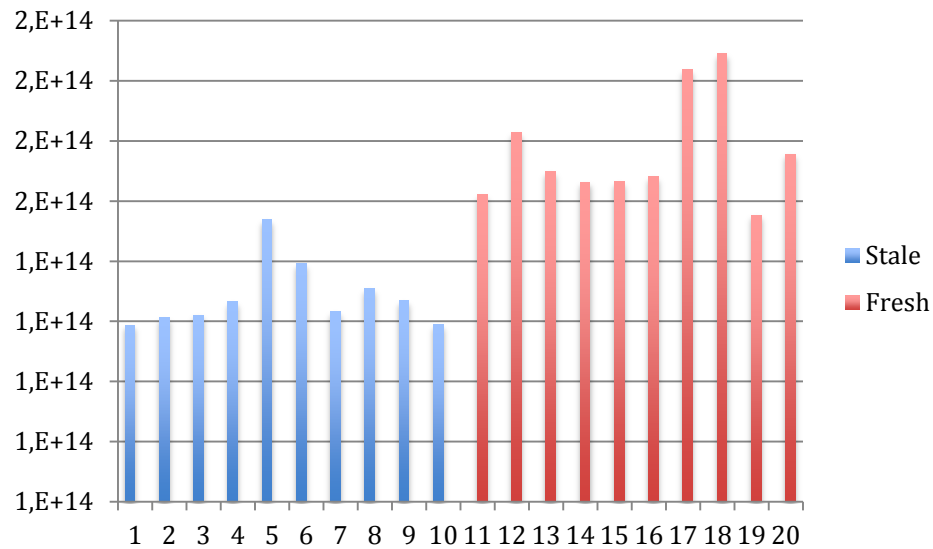


Figure 5.11 Feature 1: Normalized area of fresh and stale samples

The area covered by the fish is calculated by finding average of all the values of five regions of interest. As seen in figure 5.11 red coloured bars represent the area of fresh fish, whereas blue coloured bars represents the stale fish. In general, the area of the fresh fish is bigger than the stale fish. With this information it is not possible to completely decide freshness of fish. It is clear that additional features are required.

5.3.2 Feature 2

Firstly, the slopes of five different regions have been examined according to their freshness. From here, it was seen that each individual region is not enough to provide clear separation. But grouping the regions provides more distinctive separation between the fresh and the stale fish. Various combinations of grouping were tried

and the best result was obtained by grouping first three regions into a single region and the other two regions into another region.

Figure 5.12 shows the slopes of combined first three regions. In general slopes of fresh fish is less than the stale fish. The increase of the slope of stale fish can be described with deformation in the fish's head.

Figure 5.13 gives the slopes of combined last two regions. In general there is information for the separation of the fresh and the stale fish, but this is not as strong as first three regions. This can be explained with the physical structure of the fish head. The last two regions correspond to bony part of the fish head. Therefore deformation in the bony part is the minimum.

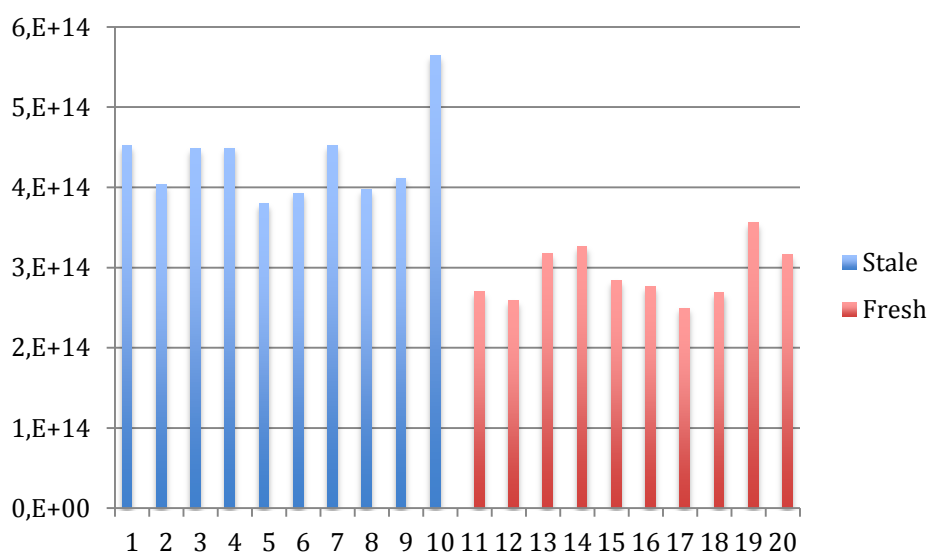


Figure 5.12 Feature 2 for fresh and stale samples

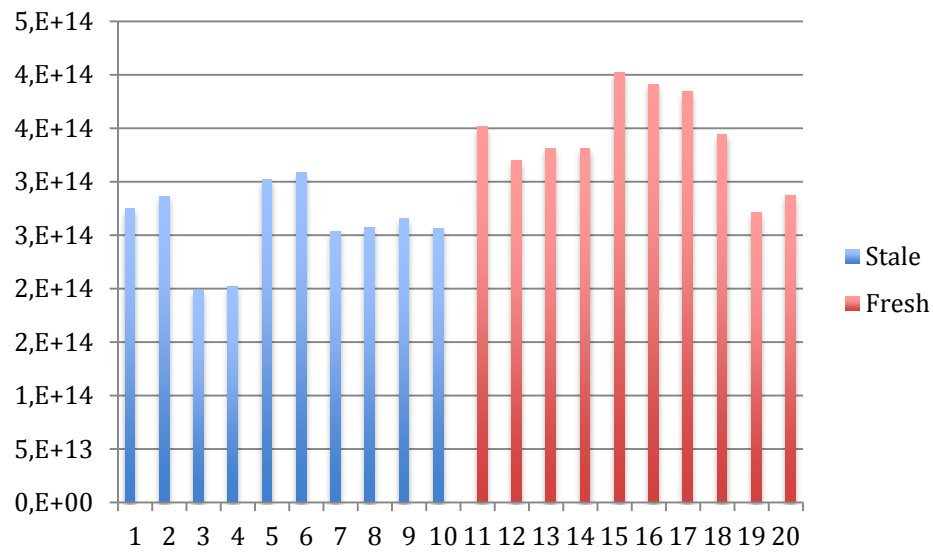


Figure 5.13 Feature 3 for fresh and stale samples

5.3.4 Colour Information

It has been observed that colour of the fish changes according to its freshness. The hue information is also used as another feature. In order to calculate hue value picture of the fish is presented to the user as shown in figure 5.14, and user selects the abdomen of the fish where spoilage begins. As shown in figure 5.14 the user selects the (X,Y) point by pointing the mouse.

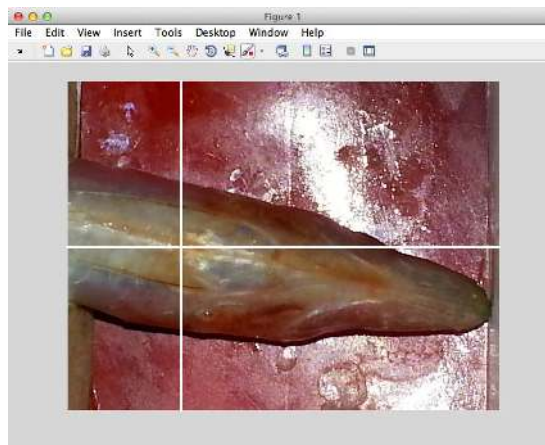


Figure 5.14 User input to select ROI for color information

A square given in figure 5.15 is determined according to the selected coordinates (X,Y) . A square with a size of 30x30 pixels was found enough to get reasonable colour information. So coordinates of square determined by centering this selected coordinates as center of the square.

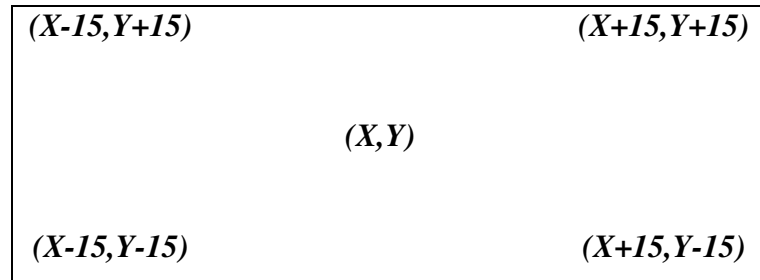


Figure 5.15 Selected square according to the user response

Selected square region is displayed to the user as shown in figure 5.16.

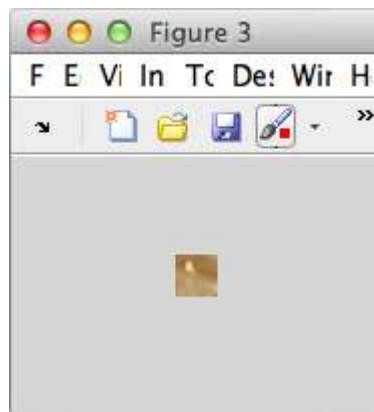


Figure 5.16 Selected Region of Interest (ROI)

Hue, Saturation and Value (HSV) model of selected area is obtained to as a new feature. Hue values of all the pixels are summed together and divided by total number of pixels to calculate average hue values of fish. Average hue values for all fish samples are shown in table 5.2.

Table 5.2 Hue value of the samples

	Hue		Hue		Hue
Fresh 1	0.62	Stale 1	0.09	Test 1	0.15
Fresh 2	0.67	Stale 2	0.07	Test 2	0.06
Fresh 3	0.58	Stale 3	0.13	Test 3	0.12
Fresh 4	0.60	Stale 4	0.13	Test 4	0.09
Fresh 5	0.64	Stale 5	0.11	Test 5	0.11
Fresh 6	0.61	Stale 6	0.09	Test 6	0.63
Fresh 7	0.56	Stale 7	0.15	Test 7	0.60
Fresh 8	0.57	Stale 8	0.06	Test 8	0.58
Fresh 9	0.59	Stale 9	0.08	Test 9	0.61
Fresh 10	0.63	Stale 10	0.14	Test 10	0.62

5.4 Fish Freshness Determination using Neural Networks

5.4.1 Neural Network Structure

In this study two different multilayer perceptron neural network (MLPNN) structures with different input sizes are used and compared. Both of the networks consisted of three layers; input layer, hidden layer and output layer. It is possible to have more than one layer in hidden layer. However, in this study single hidden layer was enough to have good classification. For both networks there are ten neurons in the hidden layer and one neuron in the output layer that indicates whether fish is fresh or stale.

In the first network there are three neurons for three different features. Second network has one more neuron for the colour information. Figure 5.17 show the neural network structure.

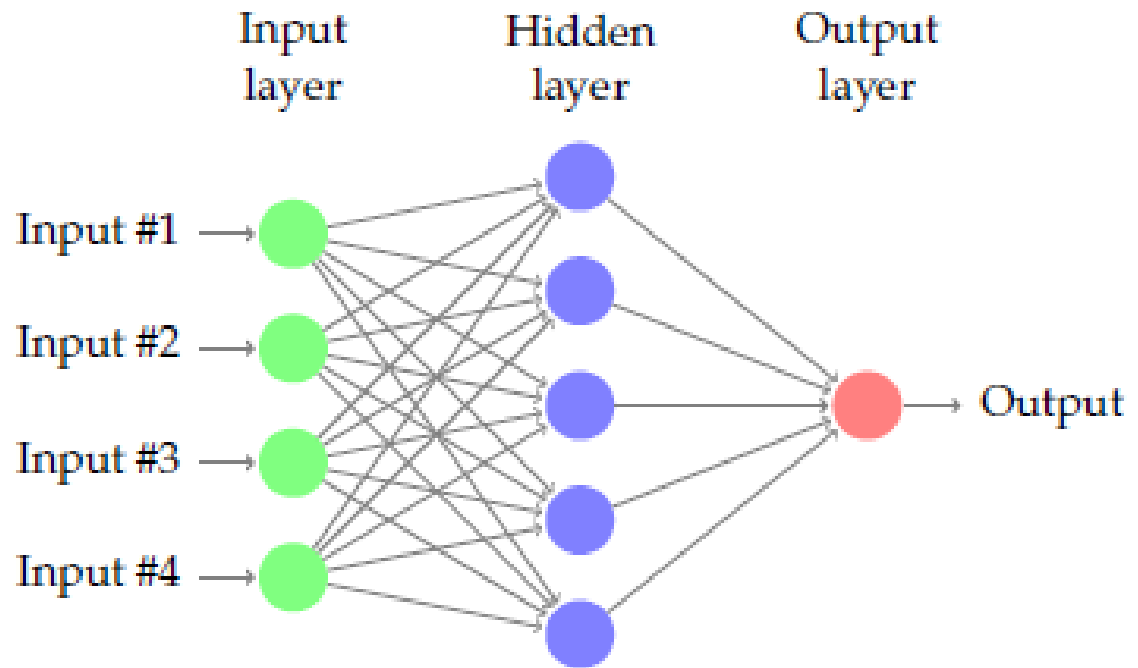


Figure 5.17 Neural network structure

5.4.2 MLPNN with Three Inputs

Three inputs, the area, combined slope 1 and combined slope 2, which give the physical information about the fish, were used to train the network.

MLPNN was trained with backpropagation and the learning algorithm is the levenberg-marquardt. 20 different samples consisting of 10 fresh and 10 stale were used in training.

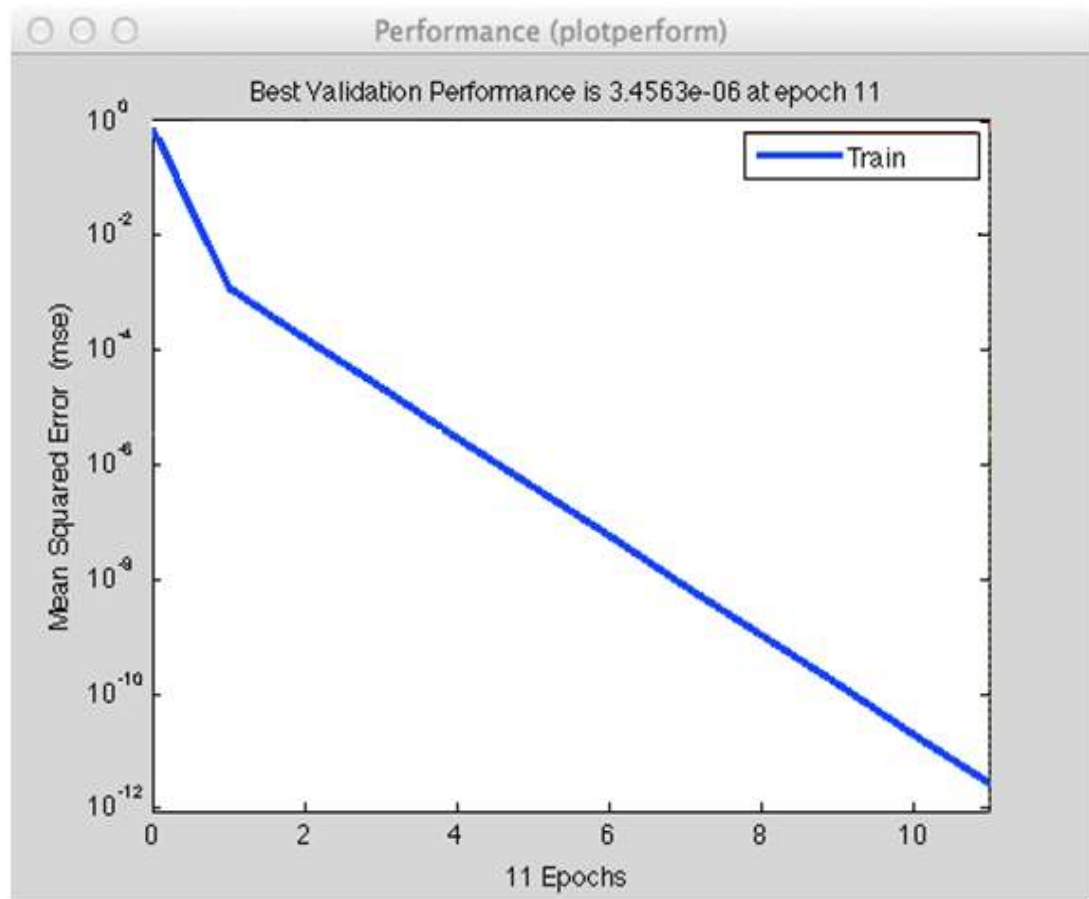


Figure 5.18 Neural network training

Desired training error was reached after 11 iterations. When the training is completed, the network then was tested with 10 different test data, five of which is fresh and the other five was stale. In this way 33% of the complete dataset has been used for testing the network.

90% of the test data were classified successfully; only single fresh fish was not classified correctly. When figure 5.9 is examined it can be seen that there is one fresh fish, which provides features similar to the stale fish. This can be simply from the physical shape of the fish or the way that the image was taken.

5.4.3 MLPNN with Four Inputs

To overcome this shortcoming it was decided to add a new feature to the neural network input. The new feature is the colour information obtained from the selected ROI on the body of the fish. In the new network the number of inputs were set as four.

MLPNN was trained with backpropagation and the learning algorithm is the levenberg-marquardt. 20 different samples consisting of 10 fresh and 10 stale were used in training.

Desired training error was reached after 7 iterations. When the training is completed, the network then was tested with 10 different test data, five of which is fresh and the other five was stale. In this way 33% of the complete dataset has been used for testing the network.

With the addition of the colour feature 100% of the test data were classified correctly.

CHAPTER SIX

CONCLUSIONS AND FUTURE WORK

In the scope of this thesis, a practical method to determine the freshness of fish is discussed. Although fresh fish is very healthy food, eating stale fish can mistreat human health.

While investigating the period of staling, some changes are noticed on the physical characteristics of the fish; the area of the fish when looked from underneath started to shrink, slopes on the head part started to decrease, slopes on the middle part started to increase and colour of the skin changed from bluish to a kind of yellowish. As these are noticeable deviations, a mobile phone with a camera was enough to sense them. No additional sensor has been used to obtain any other feature. Fish photographs are taken by a mobile phone's camera and in this study, sardines was used since it is one of the most consumed locally available fish.

In order to systematize photos, a stand was assembled to hold both the camera and the fish. Stand is made of wood and has two layers; in the first layer fish is placed between two wooden sticks, and in the second layer mobile phone is positioned into a special slot.

Photographs are taken at the resolution of 640x480 in coloured mode. No extra lightning equipment is used; required lightning is supplied by mobile phone's flashlight.

When the photos are obtained, a set of pre-processing steps is applied to images to extract some useful information related with the shape of the object; grayscale conversion, edge detection, dilation and removing unwanted edge pixels. Also colour information is acquired from the original images.

After pre-processing phase, silhouette of the fish acquired by measuring the distance of the top and bottom white pixels. In this way, outline of the fish is transferred to one-dimensional variable. The information related with the shape was extracted easily from that data.

The data related with the shape fed into a multilayer perceptron neural network and 90% of success rate achieved. With the help of colour feature 100% of the samples have been classified successfully.

In this study, classification is based on fresh and stale sardines fish and for this photographs were taken at twelve hours time intervals. For future work, smaller staling periods of the fish can be examined for example every three hours of it. After taking fish photographs in short periods, with extracting features and analysing on MLPNN, the freshness of the fish can be detected more accurately. In this way the freshness of the fish can be categorized into four classes; very fresh, fresh, average and stale. In this study color information was obtained by the help of the user. For future work, selection of ROI can be automated. Also, with the increased computational power of the mobile phones, not just acquisition of the images but whole detection process can be implemented on a mobile phone. Moreover, not only sardines but other types of fish can be used for freshness detection. For this, new features must be obtained and the network has to be trained according to the selected fish type.

This thesis, including some implementation for practical detection of fish quality and some design experience, will be a good reference for the upcoming projects.

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