KAUNAS UNIVERSITY OF TECHNOLOGY

FACULTY OF MECHANICAL ENGINEERING AND DESIGN

Madhumadi Alwar Rajagopal Dhanasingh

RESEARCH AND DEVELOPMENT OF AUTOMATIC VISUAL INSPECTION SYSTEM OF WOODEN DOWELS

Final Master's Degree Project

Supervisor
Assoc. Prof. Dr. Vidas Raudonis

KAUNAS, 2015

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FACULTY OF MECHANICAL ENGINEERING AND DESIGN
DEPARTMENT OF MANUFACTURING ENGINEERING

APPROVED BY
Head of Department
Assoc. Prof. Dr. Kazimieras Juzėnas

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Final Master's Degree Project
Mechatronics (code 621H73001)

Supervisor
Assoc. Prof. Dr. Vidas Raudonis

Reviewer
Professor Dr. Arunas Lipnickas

Project made by: Madhumadi Alwar Rajagopal Dhanasingh

KAUNAS, 2015

"RESEARCH AND DEVELOPMENT OF AUTOMATIC VISUAL INSPECTION SYSTEM OF WOODEN DOWELS"

DECLARATION OF ACADEMIC HONESTY

<u> 1 </u>   <u> June </u>   <u> 2015 </u>
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1. Darbo tema

Medinių kotelių vizualinės patikros sistemos kūrimas ir tyrimas

Patvirtinta dekano 2015 m. May mėn.11d. įsakymu Nr. ST17-F-11-2

2. Darbo tikslas

Pagrindinis darbo tikslas yra vizualinės kokybės sistemos sukūrimas, kuria būtu galima inspektuoti konvejeriu judančių medienos gaminių (kotelių) kokybę. Tikslui pasiekti darbo autorius, turi palyginti įvairias spalvines koduotes, pasirinkti tinkamiausią požymių klasifikatorių (rekomenduotina, dirbtinį neuroninį tinklą).

3. Darbo struktūra

    a) Įvadas, kuriame autorius išdėsto darbo problematiką ir aktualumą;
    b) Literatūros apžvalga, kurioje yra analitiškai tiriami įvairūs darbo tematika susiję metodai;
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    e) Eksperimentiniai tyrimai;
    f) Išvados ir rezultatai bei naudotos literatūros sąrašas turi būti pateiktas darbo pabaigoje.

4. Reikalavimai ir sąlygos

Visi eksperimentiniai tyrimai turi būti atliekami su realiomis medinių kotelių nuotraukomis. Programavimas ir eksperimentiniai tyrimai turi būti atlikti MATLAB programinėje aplinkoje. Magistro baigiamasis darbas turi tenkinti tokio tipo darbams keliamus reikalavimus.

5. Darbo pateikimo terminas 2015 m. birželio mėn. 5 d.
6. Ši užduotis yra neatskiriama baigiamojo darbo dalis

Išduota studentui _____

Užduotį gavau	Madhumadi Alwar Rajagopal Dhanasingh	_____
	(studento vardas, pavardė)	(parašas, data)
Vadovas	Assoc. Prof. Dr. Vidas Raudonis	_____
	(pareigos, vardas, pavardė)	(parašas, data)

Madhumadi, Alwar Rajagopal Dhansingh. **RESEARCH AND DEVELOPMENT OF AUTOMATIC VISUAL INSPECTION SYSTEM OF WOODEN DOWELS** Final Master's Degree Project / supervisor Assoc. Prof. Dr. Vidas Raudonis; Kaunas University of Technology, Faculty of Electrical and Electronics Engineering, Department of Automation Engineering.

Kaunas, 2015. 63 p.

SUMMARY

The purpose of this study was mainly due to a problem statement provided by a company manufacturing small wooden dowels. A visual inspection system to identify the presence of defect in the stick will be required. The focus will be in the algorithm development and proposal for the system design will be given. The previous literature assumed a particular color space to be the best and worked on selecting the effective features that could be extracted from them. The main focus of this thesis is to identify the best color space that could be used for all defect detection and grading system related to wood. Not well studied Neural Network structure for wood defect application will be used as the classifier and the reaction of the number of inputs and number of hidden units to produce effective results was studied

At first a simple and effective algorithm for finding the defect was developed. This algorithm was tested with different colour space for different number of hidden neurons. The effectiveness of each color space was found and the best color space was chosen. The best NN structure and the outputs for different neuron numbers was also found. There is no exact rule for selecting the number of neurons so far, so based on the previous assumptions and studies the neurons were selected and checked if the assumptions holds good in our case. The system was designed based on the requirements and the setup was made. The algorithm part was developed with MATLAB.

From the experiments the effective color space RGB and YCbCr produced results with 96% accuracy and the combination of them produced about 99% accuracy for the chosen neuron numbers. The not very well studied NN structure was studied. Algorithm was made effective by minimizing the time for processing as much as possible.

KEY WORDS: wooden dowels, Machine vision, color space, Neural network, MATLAB.

Madhumadi, Alwar Rajagopal Dhansingh. **MEDINIŲ KOTELIŲ VIZUALINĖS PATIKROS SISTEMOS KŪRIMAS IR TYRIMAS.** Baigiamojo magistro darbo vadovas doc. dr. Vidas Raudonis ; Kauno technologijos universitetas, Elektros ir elektronikos fakultetas, Automatikos katedra.

Kaunas, 2015. 67 p.

SUMMARY

Pagrindinis tiriamojo darbo tikslas buvo padiktuotas gamintojų, kurie gamina specializuotus medinius kotelius. Darbe yra tiriama vizualinės inspekcijos sistema. Didžiausias dėmesys darbe yra skiriamas vaizdų apdorojimo metodų taikymo galimybių tyrimams. Literatūros analizė parodė, kad dažniausiai defektų analizei yra taikoma spalvų analizė, pasirinktoje spalvų erdvėje. Pasirenkant tinkamiausius požymius galima efektyviai surasti sugadintas gaminio vietas. Šiame darbe siekiama apjungti geriausiai defekto vietą diskriminuojančią spalvų erdvę ir klasifikatorių pagrįsta dirbtiniais neuroniniais tinklais. Buvo tiriama defekto klasifikavimo tikslumo priklausomybė nuo dirbtinio neuroninio tinklo struktūros ir naudojamos spalvų erdvės.

Tyrimų metu buvo MATLAB aplinkoje sukurta programinė įranga, kuria buvo galima valdyti eksperimentų eigą. Su programa buvo galima suformuoti mokymo ir testavimo duomenų bazes, keisti spalvinę nuotraukų koduoti ir keisti dirbtinio neuroninio tinklo struktūrą. Eksperimentiniai tyrimai parodė, kad 96% klasifikavimo tikslumas buvo pasiektas naudojant atskirai RGB ir YCbCr spalvines koduotes, o jas apjungiant buvo pasiektas net 99% klasifikavimo tikslumas. Dirbtinis neuroninis tinklas buvo renkamas taip, kad tenkintų apdorojimo spartos ir klasifikavimo tikslumo santykį.

RAKTINIAI ŽODŽIAI: modieno gaminiai, kompiuterinė rega, spalvų erdvė, dirbtinis neuroninis tinklas, MATLAB.

TABLE OF CONTENTS

INTRODUCTION

Visual inspection is a very important task in quality assurance of a product. The manual visual inspection is always a dull and boring task utilising much time, money and effort. The easy and effective replacement of manual inspection is the automatic visual inspection which can think and make decision based on the inputs given.

Many complex design of the Automatic visual inspection system incorporating all the necessary sensors were designed previously, which are capable of providing highly effective inspection. Many complicated and effective algorithm based on different classification techniques which are used in defect identification were also seen. These algorithms mainly worked on selecting a random color space assumed by them to be effective and applies extensive classification and defect detection schemes to them. The idea of which colour space to be selected for defect detection related to wood defect classification was not widely studied.

The literatures on defect detection algorithms mainly used segmentation approach and Fuzzy logic because of its easy understanding. The Neural network structure was not widely used for defect identification in wood products as there is no clear properties to select the number of hidden units and hidden layers. For our algorithm Neural Network scheme will be employed.

The main aim of the work is to determine the effect of color space in wood defect detection. The experiment includes creating a simple algorithm keeping in mind the processing time and effective detection with NN scheme. The algorithm was tested with different number of hidden units to overcome over fitting and under fitting problems and to select the optimal number of neurons. The same algorithm was applied to different colour space and the best color was evaluated. From the work we will determine.

1. The best colour space that will work well for defect detection in wood based on simple features.
2. The best NN structure and the effect of the number of hidden units in producing accurate results.
3. How the combination of two best colour space will work in classifying the defect.
4. The design of the entire system will be proposed.

1. AUTOMATIC VISUAL INSPECTION

1.1. NEED FOR AUTOMATIC VISUAL INSPECTION SYSTEM

Wood getting to be a scarce source the usage of wood have to be taken care of. The wastage of wood during manufacturing of wooden products is getting common due to various factors such as internal damage in the wood, the machinery used for scrapping and modelling. Wooden products are mainly produced using hardwood lumber, however, the price of hardwood lumber has almost doubled during the last 20 years [1]. Likewise in wooden dowels manufacturing industry the end product of manufacturing is prone to factors that produce unlikely products. These damage are due to factors that cannot be overcome even with high end technology like the internal defects in wood, weak or worn parts in the raw wood etc. When these wood are sent to dowel making machine the end product can be damaged.

In most manufacturing industries, one goal is to achieve 100% quality assurance of the parts, subassemblies, and finished products, especially in mass-production industries. Product inspection is an important step in the manufacture process, and how to ensure that the quality of each product meets the standard is a challenging task. However, inspection tasks are time consuming, and mostly performed by human inspectors [2].

In a mass wooden dowel manufacturing company the end product can be damaged in some cases. Due to mass production inspection for quality control of the product becomes inefficient in certain situations. The drive towards higher productivity in the manufacturing industry in South Africa and elsewhere has highlighted the need for an improvement in product inspection [3].

Manual inspection will be time consuming and the inspection of the entire surface of the dowel can be problematic. According to a study the error tapping period for human inspectors cannot be for long periods. Maximum efficiency of error tapping can be up to 15 minutes and will reduce drastically. The number of error made depends on the complexity of task, time of day, day of week. These observation was done for inspection of printed circuit board [4]. The Experience gained in USA for PCB defect detection shows that a manual visual inspection can be expected to find only approximately 70 % of the total errors on a complex tasks [5].

On the automation of visual inspection, potential advantages have been justified. One obvious advantages the elimination of human labor, which is increasingly expensive human

inspectors are slow compared to modern production rates, and they make many errors. Other advantages of automatic operation are speed and diagnostic capabilities.

Several practical reasons for automated inspection include:

- ❖ To set free human from the dull and routine.
- ❖ To perform inspection in dangerous and in unfavorable environments.
- ❖ To cut the human labor costs.
- ❖ To analyze statistics on test information and for handling records.
- ❖ To reduce the demand for human labor who are capable of doing high skilled inspection.
- ❖ To match high-speed production with high-speed inspection [6].

Routine tasks found boring are combine with high end software and hardware to open new possibilities in knowledge processing. Very large data set are processed with highly intelligent engineering software based on unstructured commands and subtle judgments and has the ability to learn 'on the fly' with the events are a great mile stone towards automation of knowledge work [7]. Over the last 20 years machine vision has played an important role in taking the quality control of products to the next level. During this period a lot of researchers have been working in new methods and algorithms to make the process much better and efficient. It has become rare to find a mass product manufacturing company to work without some form of vision inspection system [8].

The problems in advance automation manufacturing have been spoken about in many research areas [9].Many conferences were held and research studies have been done which ultimately shows the need for industrial automation. When there is increase in productivity and improved product quality the manufactures are ready to welcome automation [10].

1.2. AVI PERFORMANCE COMPARISON WITH MANUAL INSPECTION

An attempt to find the performance of and efficiency difference between automatic visual inspection and manual inspection was done by many AVI industries. Depending on the type of the product the efficiency varied. An attempt to validate the pros and cons of automated inspection and manual inspection in [11] was made and the quality and economic efficiency of sterile products in filled container was studied. A validation of a manual inspection is not feasible due to the lack of reproducibility. Generally, the inspection process should be

automatized. On the other hand high costs for the machine and validation studies should be taken into consideration. From August 2004 to January 2005 studies were performed at Essex Animal Health Friesoythe, a Division of Essex Pharma Germany, to evaluate the efficiency of manual and automatic inspections methods.

The following Fig. 1.1 was the result produced by the research on the speed of the systems. The efficiency of the automatic inspection system was about fifteen times more than the manual system. Table 1.1 shows the inspection of production of 3.4 mio vials with the time and staff need from which we can infer the need of automatic visual inspection.
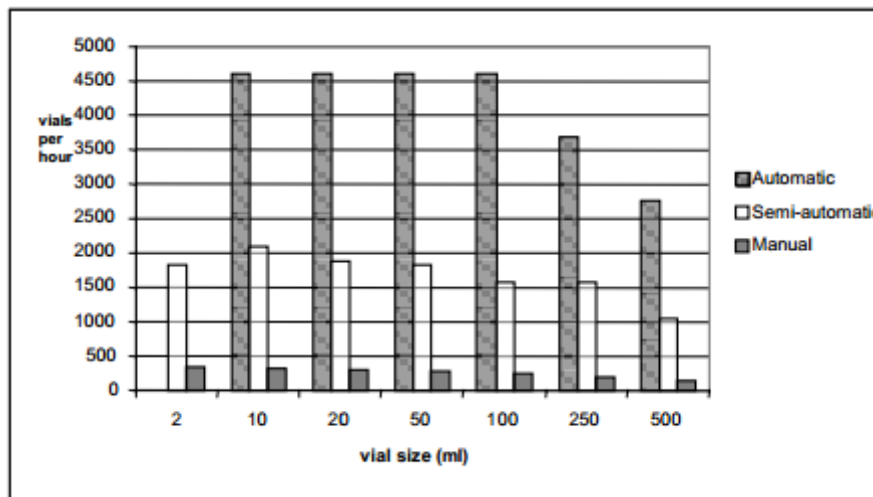

Fig. 1.1. Efficiency of the inspection systems depending on the size of the vial [11]

System	Time	Staff
Manual	13.535 h/a	13
Semi-automatic	1.799 h/a	7
Automatic	685 h/a	3

Table. 1.1 Time and staff needed for inspecting 3.4 miovials [11]

On the aspects of cost of the system a break-even analysis of automated and semi-automated inspection shows the automated system (in-line) will be the one with minimum costs after four years. The Fig. 1.2 below shows the calculation in the following diagram to only for one year.
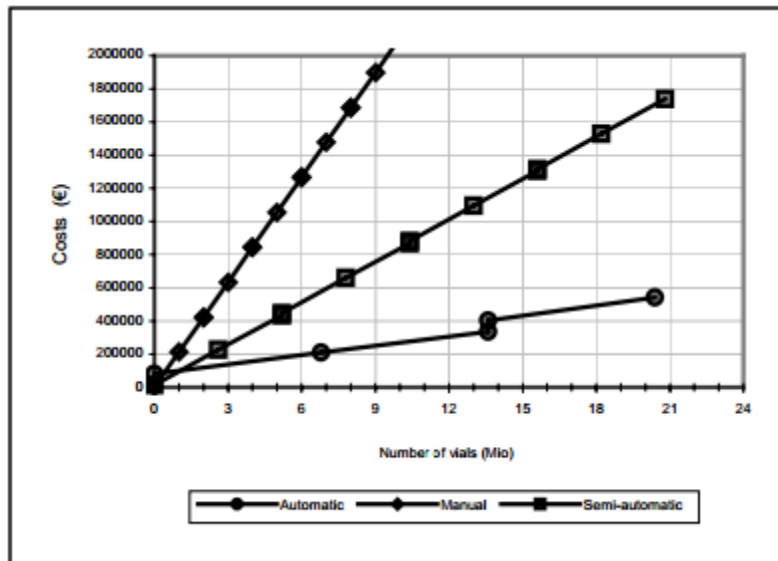
Fig. 1.2. Cost trend depending on the product vials [11]

On the whole the automatic visual inspection system has showed many advantages compared to manual inspection in terms of accuracy, efficiency, time and cost factors. The need of automatic visual inspection system for wooden dowel defect detection system becomes necessary.

2. STATE OF ART

2.1. MACHINE VISION IN DIFFERENT FIELDS

There is a massive use of machine vision systems in electronics industry, where the level of complexity in finding small defects is high. There has been so much research and techniques applied for finding the defects and they have been successfully implemented. The proposed systems for electronic industry was studied in detail and the classification of the various methods was given. The paper "A survey of AVI in semiconductor industry" by Szu Hao Huang shows in detail the various techniques and classification. It divides the process into two parallel methodologies and inspection algorithms were classified into four major categories: projection methods, filter-based approaches, learning-based approaches, and hybrid methods. The current paper presents a profile of AVI systems used in semiconductor industry. Reviewing relevant literature using the two classifications of algorithms and products can clearly determine the algorithm characteristics, and also enable companies to select proper algorithms for developing their own inspection systems for manufacturing [2].

Pharmaceutical pellet manufacturing industry had a great need to check the proper coating of the manufacture medicine pellets and to ensure that the shape of the pellets where not bad. Since such an industry would have high speed manufacturing of tiny pellets manual checking of the pellets becomes highly impossible. The proposed inspection methodology in [12] clearly describes the various parameters like shading which was considers and the parameters which were calculated to effectively monitor the coating of pellets. The robustness, reliability and speed of the system was ensured with their proposed system [12].

The work of the author [13] shows the application of visual inspection in fired ceramic tile manufacturing and grading industry. The system was developed to ensure the products are free from defects for classification process and also to adapt to material change. Rather than using standard algorithms various mathematical properties like edge detection, morphology operation and smoothing was done [13].

One other industry which needs automatic vision system for its high production rate is the sheet metal stamping industry. Metal stamped parts may have effects due to its hard stamping, bending, embossing and blanking process. According to the article [14] an improved automatic system which has good efficiency, repeatability and stability was developed in Matlab and tested on real steel images. The algorithm goes with pre-processing, color

segmentation, feature extraction, defect detection and classification. Connected component analysis algorithm was used to label the regions, once they are labelled difference in their properties are found and characterization was done [14].

Textile industry is not an exception to have an automatic visual inspection. The defects generally seen in textile industry are very minute and identification of it can be a tedious task. The above said vision systems like the electronics and tile industry have algorithms generally based on template matching and edge detection. But for vision systems for textile, wood and metal industry the parameters measured are textural features. The classifier used to inspect the textural feature of the fabric was chosen to be GMRF model. The model based computational approach was found to produce good results on real fabrics [15].

Multiple-sensor lumber scanning prototype was developed by the combined efforts of Virginia Tech and the Southern Research Station of the USDA Forest Service to demonstrate the test applicable scanning technologies. This Research and development effort has led to a patented sorting system based on the color of the wood and grain and even a defect detection system for lumber [16].

Machine vision and image processing has been used for quality control in electronics industry for several years   like checking of printed circuit board assembly lines. Many applications have been developed for security, packaging industries and elsewhere but machine vision and image processing is relatively new or underused area in the woodworking industry. The amount of manual work in woodworking industry can be reduced or even eliminated with image processing applications while at the same time increasing the quality and reducing the time.

Fruits industry makes use of machine vision for the grading system and also to check the growth rate of the fruits. The Gaussian Mixture Model (GMM) is used to estimate the parameters of the individual classes for prediction of maturity. Size of the mango is calculated from the binary image of the fruit. Finally the fuzzy logic techniques is used for automatic sorting and grading of mango fruit [17].

2.2. COLOR INFORMATION IN WOOD DEFECT DETECTION

Literature about role of color and the color space in wood defect detection was found to be many, each stating a particular method for detection of defect [18]. *Brunner et al. 1990* showed that the color differences between the sapwood and heartwood and the color difference of the surface feature of the earlywood and latewood is important in imaging.

The importance of color feature in wood defect detection was studied in [19] were Bayesian classifier was used for defect detection using the color properties of the defects in maple. The RGB color scheme was used for this. The color homogeneity of spectral reflectance of pine wood and its defect was studies and the results of the study was able to detect the defect but was not able to classify the defects due to complex spectral reflectance [20].

A segmentation approach to defect detection based on the color information for southern pine, red oak and yellow-poplar was used and Information from 31 histogram was used in this segmentation and it was performed with few samples [21]. *Butler et. al (1993)* [22] even used the color value of the RGB color space for defect detection by using R-B/2 as color feature he still has classification error which was unexplained but it just showed the usefulness of the color space.

The L*a*b color properties of heartwood, sapwood was measured using a calorimeter in [23] this method was not able to detect the entire defect area and also to differentiate them [24] [25] used the color information and the color feature for identifying defects in spruce. The color features used was the histogram of the RGB color channel intensities. The principle component analysis classifier was used with the spectral reflectance measure from a spectrometer the spectral reflectance curve for each feature type was modelled and this method has a serious drawback as it could not be applied to commercial application.

To identify the Knots present in clear wood *sadoa and takita et. al 1992* used color information. The color information was proved to provide good results in detecting knots. *Sugimori et. al 1993* also tried to recognize the sloped grain present around knots for which he proposed color information.

The *João Faria et. al 2015* used the histogram values that is the color information combined with fuzzy logic technique for grading system in wood. In this he extracted the features from the HSV and L*a*b scheme which was a random selection on the fact that the

features extracted will give the system the capacity to distinguish images that looked similar to human eye.

Seppo Enarvi et. al 2006 in his research on identifying defects in wooden logs used RGB color space in finding the defective part but when the background became dark it was inappropriate for the color space to produce good results so then they moved to HSV to use the illumination component.

In literature *Adel Ziadi,et. al 2007* the author used color image segmentation to sapwood assessment. In this algorithm he used neural network scheme and the colour space chosen was the RGB and the HSV which was based on analysing the histogram peaks. The results produced was satisfying. Weiwei Song et.al 2015 used the same colour spaces RGB and HSV for finding the defect in wood material but they used SVM for this process.

Selman Jabo et. al 2011 also used the same HSV and L*a*b colour spaces for extracting the features in wood defect detection using supervised learning combined with adaboost technology for identifying the defects. The results produced by them was effective but they failed to show the effect of this colour space in defect identification.

For wood defect detection scheme there was no much literature about the other color space that would be effective in defect detection but for other defect detection mechanism like vegetable and fruit grading there is much literature on different color space.

To conclude with the previous studies the color space was first selected and then the feature which will effectively suite for the particular color space was found rather than showing how a particular feature will react to the different color space. Most of the classification done using color feature was based on histogram and segmentation approach and the main colour space used were RGB, HSV and L*a*b. Studies on the effect of all the colour space available is needed for better understanding.

3. THEORITICAL BACKGROUND ON FEATURES AND CLASSIFIERS

3.1. IMAGE FEATURE

Feature extraction and representation is a crucial step for identifying the defect. How to extract ideal features that can reflect the intrinsic content of the images as complete as possible is still a challenging problem in computer vision [26].

The features required for the classification of the defective part of the wooden dowels under study are broadly classified into two the color feature and the texture feature. The color feature are used when there is distinct variation in the color space of the region of interest as said the defective region is said to have color abnormalities than the normal region of the wooden dowels. The spatial arrangement of the colors or intensities in the image is seen in texture features.

3.1.1. Color Space Feature

Color is one of the most important features of images. Color features are defined subject to a particular color space or model. A number of color spaces have been used in literature, such as RGB, HSV, LUV and HMMD [27]. Color can also be perceived as per its brightness, hue and saturation. Brightness is the perceived luminance. The hue refers to the amount of redness, greenness of the image. Saturation varies and is stronger as more and more white light is added to a monochromatic light. All of the three components change when either the wavelength, the intensity, the hue, or the amount of white light in a color is changed [28]. RGB image is based on primary relative color. This space does not represent color as perceived and analysed by the human visual system. A basic factor known is that the human visual system uses three paths one for achromatic information and two for chromatic contrast signals [29]. Color information has been used in two ways. In the first case, the chrominance and luminance values computed from the xyY, HIS and RGB color spaces are used. In the second case, all the three color channels of the perceptually uniform color spaces L*a*b* and HSV are considered [30].

RGB is a familiar color space often used in image processing, but it suffers from an important drawback for many robotic vision applications. In robotic soccer game the color feature is marked for identifying the environment (e.g. the ball might be painted orange). The classification software should be made robust in variations in the brightness of illumination, so

it would be useful to define "orange" in terms of a ratio of the intensities of Red Green and Blue in the pixel. This can be done in an RGB color space, but the volume implied by such a relation is conical and cannot be represented with simple thresholds. Luminance is coded in two of the dimensions (H and S for HSI or U and V for YUV) while intensity is coded in the third. Thus a particular color can be described as "column" spanning all intensities. These color spaces are therefore often more useful than RGB for robotic applications [31]. The L*a*b* is a CIE (Commission Internationale de l'Eclairage) recommended approximately-uniform color space. The original space is the RGB which is converted to an intermediate CIE XYZ space and then to the L*a*b* space [32].

Many color features like color histogram [33], color moments [34] color coherence vector [35] and color correlogram [36] are proposed for various image processing application in literatures. The features are to be extracted from the different colour space. The consolidated pros and cons of the various color methods that are used so far are shown in the following table.3.1 the list of various colour model and how it is represents a pixel will be shown in the following sections.

Table. 3.1. Comparison of different color descriptors [26]

Color method	Pros.	Cons.
Histogram	Intuitive, computation simplicity.	No spatial information, high dimension, sensitive to noise.
Color moments	Compact, robust.	No spatial information, not enough to describe all colors.
Color coherence vector	Spatial information.	High computation cost, High dimension.
Correlogram	Spatial information.	Very high computation cost, sensitive to noise.
Dominant color descriptor	Compact, robust.	Needs post processing for spatial information.
Color structure descriptor	Spatial information.	Sensitive to noise.
Scalable color descriptor	Compact on need, Scalability	No spatial information, Less accurate

3.1.1.1. RGB Color Space

During image acquisition all the image are RGB. RGB is a Cartesian coordinate system which is cube as shown in Fig.3.1 RGB is the representation of three values red green and blue as three array and with each of the three value forming a single pixel. RGB suffers from the effect of luminance but it is also suitable to eliminate some colors which are not needed. The previous algorithms that were applied for wood defect detection [18] was main on just RGB and grey scale images. Butler [22] showed that the use of RGB color information for pixel based defect detection increased the accuracy to 20% of the grey scale one.
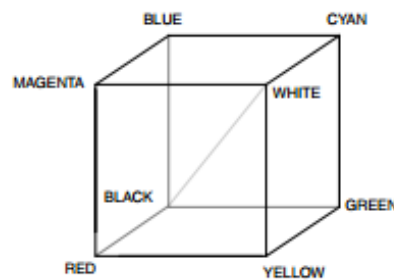
Fig. 3.1. RGB color cube [37]

3.1.1.2. LAB Color Space

LAB space has three parameters. It is much difficult than RGB space to describe and to visualize it. The fig.3.2 Shows the L*a*b color space representation. L has a range of 0 to 100 and for each value of L a picture with specific color range can be drawn. The A represents a horizontal dimension crossing the L axis at the centre and it varies from green in one end to magenta in the other end, and b is the balance between yellow and cyan. In detection scheme like the retinal wedge identification uses LAB scheme to eliminate the effect of luminescence component. Most important feature of this color space is that this is device independent. Device independent means it produces same colors across different devices.
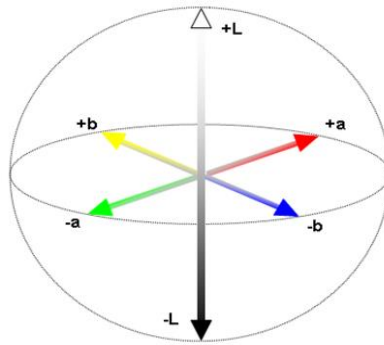
Fig. 3.2. The L*a*b Color representation [38]

3.1.1.3 HSV Color Space

HSV space has three components the Hue Saturation and Value and it is a nonlinearly transformed RGB space. Saturation is the amount of white can also be said as the purity of color. Value is the brightness of the color. Hue ranges from 0 to 360°C. The HSV space were combined with fuzzy logic technique in grading of wood and was found to be good and effectiveness increased with increasing size of the window [39]. The Fig 3.3 Shows the representation of the HSV color space. The transformation of the RGB color space into HSV will have the color in the hue.
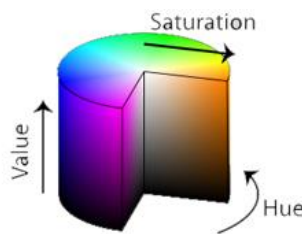
Fig. 3.3. Representation of HSV color space [39]

3.1.1.4. YCbCr Color Space

YCbCr generally has more advantage than the RGB & HSV model as it uses chrominance values. Similar to HSV, YCbCr separates chrominance information into two channels Cb (blue chroma) and Cr (red chroma), and intensity into a third channel Y. The below matrix is used for the conversion of RGB to YCbCr space. YCbCr color space is used for skin detection popularly of its effectiveness. This space is just the other way of encoding the RGB color space. From Fig 3.4 shows that the chrominace B and the chrominace R are separated.

13

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$
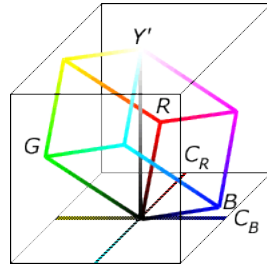

Fig. 3.4. Representation of YCbCrcolor space [40]

3.1.1.5. YIQ Color Space

This color model was adopted by National Television Standard Committee (NTSC) for color TV broadcasting [41]. This color model uses the visual sensitivity in the luminance change than hue or saturation change. I and Q stands for "In phase" and "Quadrature phase". And also I component represents orange cyan axis and Q component the magenta green axis. The conversion matrix from RGB to YIO is given below. From the Fig 3.5 it is seen that the YIQ model is much similar to YCbCr in orientation and representation.

Y=Luminance grey scale information, I=Hue

Q=Saturation

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$
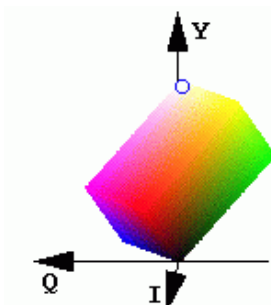

Fig. 3.5. Representation of YIQ color space [41]

3.1.1.6. XYZ COLOR SPACE

The most common standard used in graphics is the CIE XYZ color space. Like LAB color space XYZ color space is also device independent. XYZ is typically used to report the spectral response of a sample measured by a colorimeter or a spectrophotometer. This color space has not been so much for defect detection by image processing. The XYZ space representation as in Fig 3.6 is not RGB they are the extrapolations of RGB created. X Y and Z represents a tri stimulus value which take the short middle and long wavelengths of the action of cone cells in the eye.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = 1/0.17697 \begin{bmatrix} 0.49 & 0.31 & 0.20 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00 & 0.01 & 0.99 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$
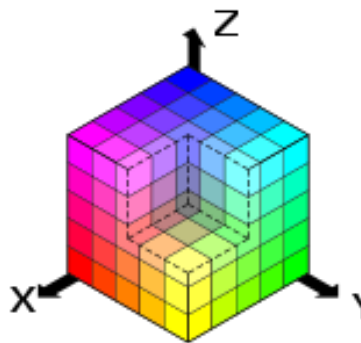
Fig. 3.6. Representation of XYZ color space [42]

3.1.2. Texture feature

Texture of an image is yet another useful characterization in image processing. It is generally believed that human visual systems use texture for recognition and interpretation. The colour information on an image is just a pixel property. Texture is a feature that should be measured with a group of pixels together. A wide range of techniques for extracting the texture features have been proposed in literatures [18]. Texture features can be extracted from spatial or spectral characteristics of the image. In spatial features the pixel statistics are computed in spectral features the features are extracted from the frequency domain of the image. The comparison of pros and cons of spectral and spatial features are shown in the following table. 3.1.

Table. 3.1Comparison of spatial and spectral texture features [26]

Texture method	Pros.	Cons.
Spatial texture	Easy to understand, features can be extracted without losing information.	Sensitive to noise and distortion
Spectral texture	Robust, Less computation	Need imagr region with sufficient size, has no semantic meaning.

Texture features extracted from spatial domain were studied in detail in [43] and the features were called Haralick features. The procedure suggested by them for obtaining textural features in image is based on the assumption that the texture information on an image is contained in the overall or average spatial relationship which the grey tones in the image have to one another. The texture information is adequately specified by a set of grey tone spatial dependence matrices which were computed for various angular relationships and distance between neighbouring resolution cell pairs on the image. A set of 28 textural features were extracted from grey tone spatial dependency matrices.

3.1.3. Fusion of color and texture features

In the method for texture classification by both the color and texture features were combined and effective results were produced. The original image was converted to HSV space from the Hue and saturation channel the color features mean and standard deviation were obtained. From the value region co-occurrence matrix was computed and five Haralick featured homogeneity, contrast, correlation, entropy, and local homogeneity were calculated [44].

The approach proposed by [44] is to use a fusion of some efficient color, texture and shape descriptors with Bayesian networks classifier to allow automatic annotation of different image types. They proposed an automatic image annotation that merges some descriptors in a parallel manner to have a vector that represents the various types of image characteristics. The performance of the proposed method has been experimentally analysed. The successful experimental results proved that the proposed image annotation system gives good results for image that are well and properly segmented.

3.2. IMAGE FEATURE REPRESENTATION

Selecting the feature required for classification is one important process but how to extract the image feature for effective classification is a big challenge. In general, there are mainly three methods [26]to transform an image into a set of regions: regular grid approach, unsupervised image segmentation and interest point detectors. Fig.3.7 illustrates the regions obtained by these three methods, where (a) shows the original image, (b) gives the image segmented by a regular grid, (c) provides the image segmented by the JSEG [45], and (d) outlines the salient regions detected by the Difference of Gaussian (DOG) [46] detector.
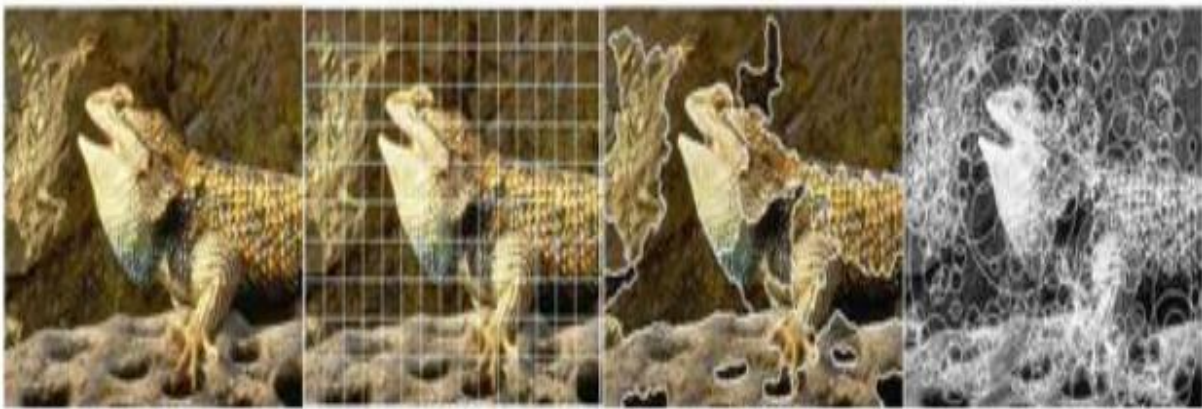

Fig. 3.7. The image feature extraction by regular grid approach, segmentation and DOG approach [26]

As the representative work of using both global and local image features, Chow et al., utilize a two-level tree to integrate both global and local image features for image classification, in which the child nodes of the tree contain the region-based local features, while the root node contains the global features. The following Fig. 3.8 shows the representation of image contents by integrating global features and local region-based features [47].
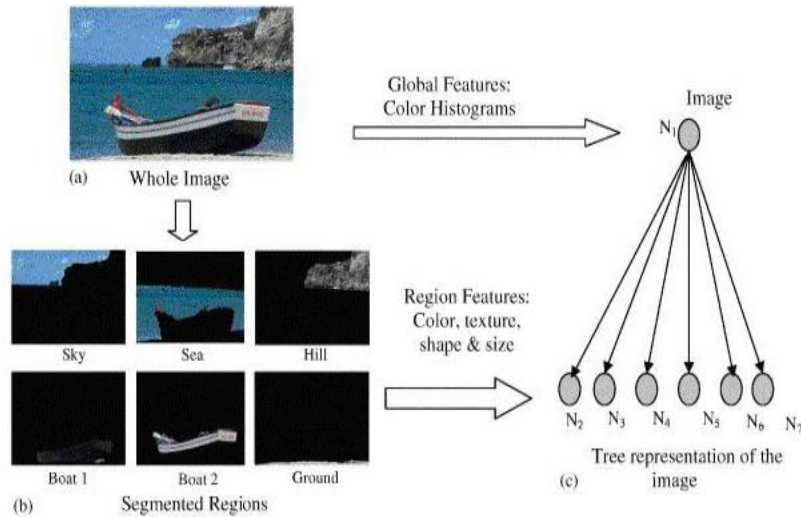
Fig. 3.8. Combining global and local features [47]

3.3. CLASSIFIERS USED FOR DEFECT DETECTION

The features extracted by any of the above method should be sent into a system which will identify the differences in the parameter values and will classify them these are called the classifiers.There are three major groups of classifier used, they are fuzzy logic, Artificial neural network (ANN) and support vector machine (SVM).Besides them, there are also other less popularlyused classifiers or classification algorithms

3.3.1. Fuzzy logic

Fuzzy logic (FL) is an easy and convenient approach for mapping an input space (referred as a universe of discourse) to an output space. In other words, mapping inputs to their corresponding outputs, such as in a general PR system where the inputs can be the patterns and outputs are the classification classes. Applying a FL approach to an image processing system brings FL properties such as: 1) great flexibility, due to the ease of modifying or adding more functionality to the system; 2) great tolerance of imprecise data; 3)experience of human experts can be used as a scaffolding for FL; 4) FL is based on natural language; natural language has evolved over the centuries to be convenient, easy and efficient, therefore it is safe to assume that FL is also easy to use when compared to other methods such as NNs [48].

Fuzzy image processing is the collection of all approaches that understand, represent and process the images, their segments and features as fuzzy sets. Fuzzy image processing has

three main stages: image fuzzification, modification of membership values, and, if necessary, image defuzzification as shown in Fig. 3.9. The fuzzification and defuzzification steps are due to the fact that we do not possess fuzzy hardware. Therefore, the coding of image data (fuzzification) and decoding of the results (defuzzification) are steps that make possible to process images with fuzzy techniques [49].
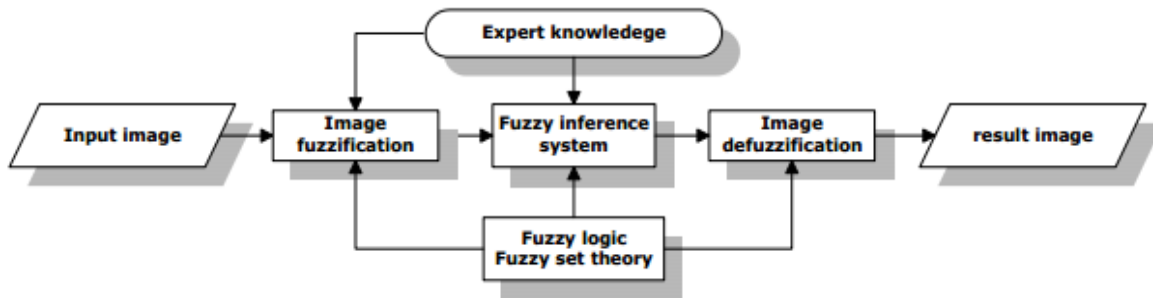

Fig. 3.9. General Structure of fuzzy image processing [49]

3.3.2. Self – organising map

Self-organizing map (SOM) -based classifier and user interface scheme is proposed for a compromise between supervised and unsupervised approaches. Thesolution supports labelling of the samples, simplifies the retraining whenever the material or imaging conditions change, provides an intuitive user interface, and is computationally attractive for real time implementations [50].

SOM consists of grid neurons, or nodes, that are associated with a model of a data vector. The SOM attempts to represent all the available observations with the nodes of themap. An important property of the SOM is that it projects similar data vectors close to each other and dissimilar ones far from each other in the topology of the map. In the pure form, the SOM defines an "elastic net" of points that are fitted to the input signal space to approximate its density function in an ordered way [51]. The color machine vision system technique developed by [50] uses SOM as classifier and uses color R, G and B features for classification and finds effective results.

3.3.3. Neural Network

ANN is a parallel distributed processor that has a natural tendency for storing experiential knowledge. They can provide suitable solutions for problems, which are generally

characterized by non-linear ties, high dimensionality noisy, complex, imprecise, and imperfect or error prone sensor data, and lack of a clearly stated mathematical solution or algorithm. A key benefit of neural networks is that a model of the system can be built from the available data. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm [51].

For our defect detection scheme NN is employed to find the defect, hence the basics of the NN will be overviewed. The building block of an NN is a neuron it has many inputs and one output. Inside the neurons the inputs are weighted and added and the result is transformed by a transfer function into the output. Functions like sigmoidal, step, hyperbolic are used as transfer function to get output [52].
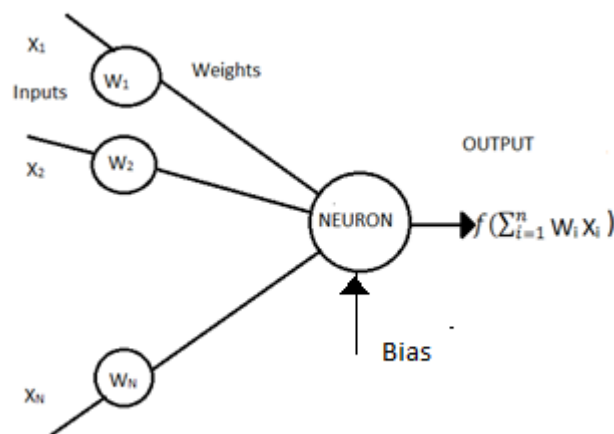

Fig. 3.10. Structure and functioning of single neuron

To understand the working of the neural network a simple feed forward algorithm is studied. The structure of the NN is shown in the Fig.3.10. The neurons are grouped as layers and the output of a neuron in a particular layer will be connected as input to the other layer but not to the neuron in the same layer. The layer which accepts the initial input is the input layer and the final layer which gives output is output layer all the other intermediate layers are called the hidden layer of the NN. The neurons in NN are fully connected which means that every single neuron is connected to all the outputs of the previous layer or to the initial inputs as shown in the Fig 3.11 [53].

The weights associated with each neuron are updated with a learning rule. In a particular neural network all the neuron will work identical to each other as they will use the same formula

to compute the output and the weights. In a feed forward network structure there is no circular information transfer paths, the information flows in steps from the input to the output. The learning algorithm employed to a NN classifies into two broad classification they are [54].

1. Supervised learning
2. Un Supervised learning:

In supervised learning the input to the network is given and the output is computed. The input is compared with the output desired for the particular input global error function is computed, with this the weights are updated to move the output to the desired output. There are tools like MATLAB to work on the image acquisition processing and training of NN. The training of neural network can take from few minutes to even days depending on when the NN is converging to give the correct answer. It could happen that NN never learns because the input data does not contain the specific information. At the present scenario supervised classification is widely known and used.

In unsupervised learning the network will be given inputs but not their desired outputs. The function of the NN is to decide what features it has to use to group the input data. Unsupervised learning is not well understood at it takes its own features these can be seen in the future used in science friction robots to learn as they encounter things [55].
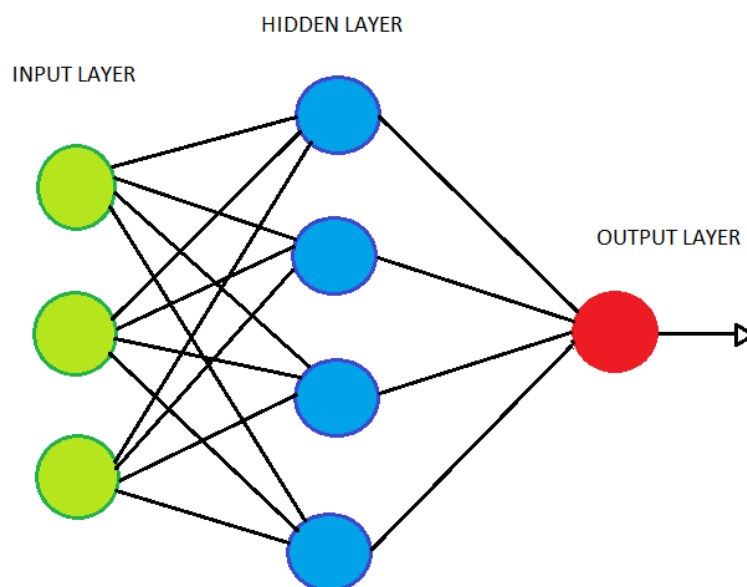

Fig. 3.11. Simple NN structure

4. PROPOSED ALGORTHIM FOR DEFECT DETECTION AND DESIGN OF SYSTEM

An overview of all the previous techniques was discussed in the previous section. In this research a machine vision system to find the defect wooden dowels will be developed and the main focus will be on the algorithm for identifying the defect. For this research a complete analysis of various color space that could be used for defect identification will be done. The color space that will best suit for defect detection in wooden dowels will be found and will be evaluated in terms of its accuracy. The classifier used for classification is the neural network scheme. The previous algorithms for defect detections in wood are generally based on segmentation approach, fuzzy logic and the support vector machine. There was no literature as studied which uses neural network well and to find the effective construction of a neural network with perfect number of neurons. The Fig 4.1 shows the presence of defect in the stick that is our problem statement.

The successive steps that will be followed in the our experiment are

1) Image acquisition and data base creation.
2) Pre-processing.
3) Feature extraction.
4) Post-processing.
5) Evaluation.
6) Design of the system.

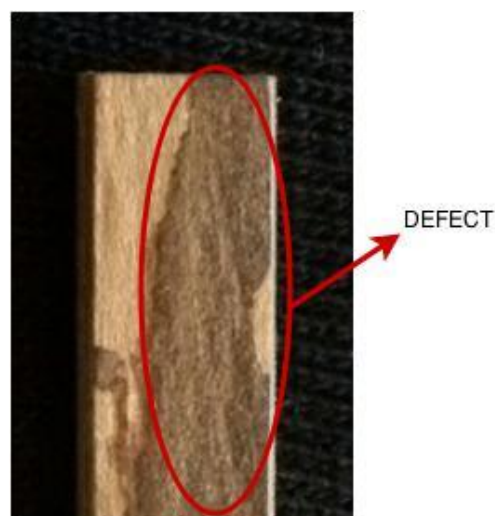**Fig. 4.1. The defective wood showing the defect present**

4.1. IMAGE ACQUISATION AND DATA BASE CREATION

The image was caputure using a camera of specification 13MP, 4128*3096 pixels with additional lighting from LED .To select the back ground color of the image the histograms of the good, bad regions were studied. The following figures are the good and bad histograms showing the Red Green and Blue channel separately. When the histograms are closely observed the bad sample has a lot of red pixels with higer pixel value in the range 150 to 200 that is it has more of red concentration and the number of blue pixels are higer compared with red and green Fig 4.2. a) and b). And when good sample histogram is studied the range of green pixels are quite less between 130 to 160 compared to red and blue. So the back ground region was selected to be pure green 245 to 255 pixel value rather than red or blue for effective classification.The Fig 4.2. c)final image capture and which will be used for processing. Once the image data base is created the regions of the defective , non defective and background Fig 4.3. are cropped and made into a separate database. This database of samples will be used for training the neural network.
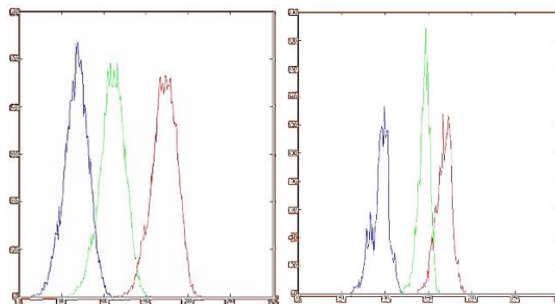
a)Histogram of defective sample b)Histogram of non-defective sample
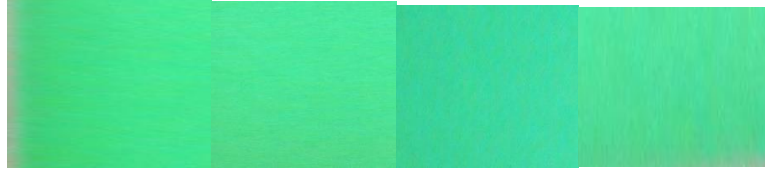

c)Final image created

Fig. 4.2. Image background selection

a)Non-defected region samples

b)Background samples

c)Defective region samples

Fig. 4.3. Data base of samples. a)Non defected region samples, b)Background samples, c)Defective region samples

4.2. PREPROCESSING

4.2.1. Normalising

Due to variation in the light during capturing of the image the surface of the stick gets illuminated this is a challenge for this research. Due to illumination as shown in fig.4.4. the defected areas have highly white pixels. This can lead to misclassification hence the input image is required to be normalised. The input image be I and (i,j) represent the pixel in the ith row and j^{th} column and r , g and b represents the red green and blue channel respectively.The subscript n represents the normalised value.The formula used for normalising the image is

$$I_{rn(i,j)} = [r(i,j)/(r(i,j)+g(i,j)+b(i,j))]$$

$$I_{gn(i,j)} = [g(i,j)/(r(i,j)+g(i,j)+b(i,j))]$$

$$I_{bn(i,j)} = [b(i,j)/(r(i,j)+g(i,j)+b(i,j))]$$

$$I_{n} = [I_{rn}(i,j),I_{gn}(i,j).I_{bn}(i,j)]$$

Fig. 4.4. Illuminating region in the input image

There is an expectional condition that has to be taken care of when the image is completeley black (0,0,0) the summation in the denominator becomes zero making the normalized value to become infinity.This can be over come by adding a 1 to the denominator value which will not make a big diffence in the outputs. Hence the euations becomes.

$$I_{rn(i,j)}=[r(i,j)/(r(i,j)+g(i,j)+b(i,j)+1)]$$

$$I_{gn(i,j)}=[g(i,j)/(r(i,j)+g(i,j)+b(i,j)+1)]$$

$$I_{bn(i,j)}=[b(i,j)/(r(i,j)+g(i,j)+b(i,j)+1)]$$

4.3. FEATURE EXTRACTION

From the database required features were extracted and the neural network was to be trained. Since the main area of the research is to find the effective color space that can be used for defect detection, the features which we are going to analyse are kept simple which will directly relate to the pixel value and shows the direct influence of the color space in defect detection. The features that directly relay on the color values are the color moments of the image.

The color moments are measures that can be used to differentiate images based on their features of color. The calculated color moments provides a measurement for color similarity between images. The values of similarity will be used to find the defective part of the image.The basis of color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. It therefore follows that if the color in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color.

Stricker and Orengo uses three central moments of an image's color distribution. They are Mean, Standard deviation and Skewness [56]. Likewise we are using the mean and the pixel value of connected 9 neighbouring pixels as features. An image therefore is characterized by 3 moments 1moment for eachcolor channels for mean. The mean E_i is given for the three channel i=3 is represented as.

$$\text{MEAN: } Ei = \sum_{N}^{j=1} \frac{1}{N} Pij$$

Where the ithcolor channel and the jth pixel in the Image P will give the mean E. The mean of a set of 9 (3*3 window) neighbouring pixels were taken and the point moved from each pixel in the entire image.

4.4 NN TRAINING AND OUTPUT

From the database created the individual images were accessed and was split into its consequent channels. The individual channel is a 2D matrix of pixel values. The features were extracted from this individual channel for the defective, non-defective and background samples. From these values the training vectors were created. The vectors has the features of all the background values followed by the defective values and finally the non-defective values. The training vector should have a target vector for the neural network to produce an output based on the trained values. The target vector will identify our region of interest the defective part. The length of the training vector and target vector should be the same. Every pixel value in the training set should have a target set. This two vectors together are given to the neural network for its training. The training vector is shown below where c1, c2, c3 represents the channel 1, 2 and 3. The number of background values be N, number of defective values be M and the number of non-defective values be K in each of the three channel.

Once the NN is trained the image that has to be tested for the presence of the defect is fed to NN. The image is again done with the same procedure as for training by splitting it into individual channel and extracting the same features as given for training set and then an vector of features for the individual channel is made. This input vector is given to the trained neural network for classification and the NN produces an output based on the target values. The output is a grey scale image where the defective part is shown with white.

Training Vector

$$= \begin{bmatrix} \text{Background Features c1} & \text{Defective Features c1} & \text{NonDefective Features c1} \\ \text{Background Features c2} & \text{Defective Features c2} & \text{NonDefective Features c2} \\ \text{Background Features c3} & \text{Defective Features c3} & \text{NonDefective Features c3} \end{bmatrix}$$

$$\text{Target Vector} = [\text{Zeros (N)} \quad \text{Ones (M)} \quad \text{Zeros (K)}]$$

$$\text{Input Vector} = \begin{bmatrix} IMAGE\ FEATURE\ C1 \\ IMAGE\ FEATURE\ C2 \\ IMAGE\ FEATURE\ C3 \end{bmatrix}$$

4.5 POST PROCESSING

The results produced by the NN will be a grayscale image N1 this image has to undergo some procedure to extract the information needed for rejection of the stick. There are several ways to do the post processing of the image. The steps used by in the research is listed below

➢ Thresholding
➢ Morphological operation
➢ Region properties

4.5.1. Thresholding

The process of dividing the pixels in the image into the background or the object classes based on the grey level value of each pixel compared with a selected parameter called the threshold. Various thresholding schemes have been studies and published [57].There are two common methods of thresholding the local and the global threshold. In local threshold value of each pixel is selected based on the information in the neighborhood pixels. In global thresholding a single threshold value will be used for the entire image. The latter is used for out technique where a single threshold is set for the entire image.

For the input grayscale image N1 if the grey level value N1(x,y) of the pixel is lesser than the threshold value T then the value of that particular pixel will become zero else the value of the pixel is 1. Where the resulting image produce is a binary image N2(x,y)

$$N2(x,y) = \begin{cases} 0 & if\ N1(x,y) < T(x,y) \\ 1 & Otherwise \end{cases}$$

The threshold of the image is adjusted between 0.6 ~ 0.9 and checked visually for different grayscale images. An optimum value of threshold that holds good for varying results were 0.8. This threshold value was fixed constant for all the images in the future. There are many thresolding algorithms like Otsu global thresholding and Niblack's and Sauvola's local adaptive thresholding [58].

4.5.2. Morphological Operation

Morphology is a technique of image processing which uses structuring element on an input image to create an output image of same size. The thresholded image N2 are processed with 3 morphological operation [59]

➢ Erosion
➢ Morphological closing
➢ Filing holes

Erosion

During erosion the pixels regions in the image which has very tiny edges will be removed. After thresholding there could be some broken pixels, these pixels are scattered or found in the border of the white region. Erosion is first done to remove the scattered white pixels. Erosion of the image by the structuring element S is given by $N2\Theta S$ where N2 is the thresholded image. The result of dilation is image *N3*.

$$N3(x, y) = \begin{cases} 1 & if\ S\ hits\ N2 \\ 0 & Otherwise \end{cases}$$

Morphological closing

Morphological closing is the process of dilation followed by erosion. After erosion in the previous steps there is no leftover scattered foreground pixels now the entire defect is found in large groups. These group of pixel are applied with dilation followed by erosion. The structuring element *S1* used is a disk shape this is used to preserve the curved boundaries of the foreground pixels.Morphological closing attempts to join large pixel groups by doing the process of dilation and then shaping it up by eroding them. The result of morphological closing will produce smoother and combined defect segregation and the image is *N4*.The function in MATLAB imclose will do this process of closing with the specified structuring element. The following equation shows the operation of morphological closing where represents dilation and $\ominus$ represents erosion.

$$N4 = (N3 \oplus Sl) \ominus Sl$$

Filing holes

The image N4 is now processed to fill the small holes present in it. This filling is done to encapsulate the defective region as a whole and it will be much effective in calculating the area of the defective part. The inbuilt MATLAB function imfillis used to do this process of filling holes. The following Fig.4.5 will show the output produced after each step of post processing unit.
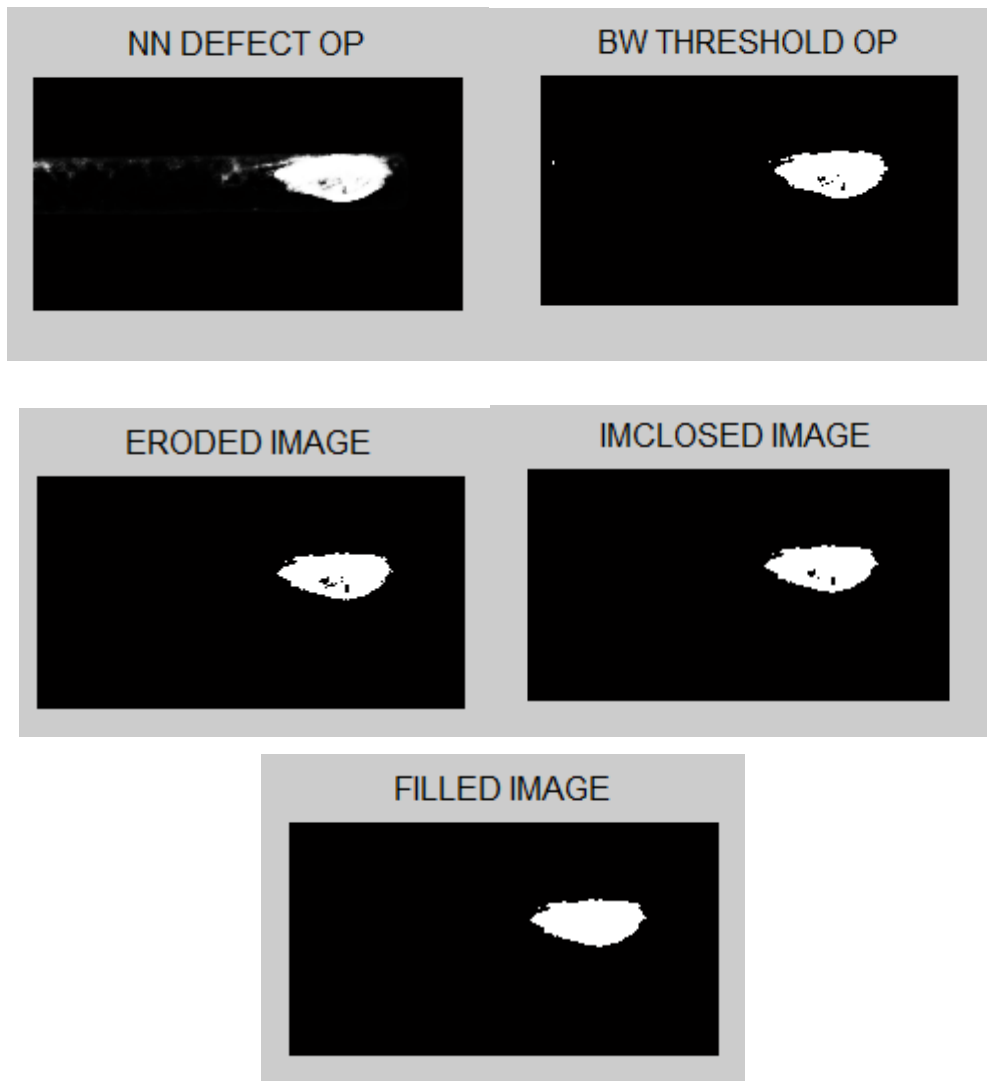

Fig. 4.5. The image obtained in different parts of algorithm N1, N2,N3, N4 and N5 from the top left.

4.5.3. Region Properties

Now from the resulting image the properties needed for analysing will be extracted. In our case the area of the foreground pixel is the important parameter to identify the defect. Other properties like centroid. Perimeter are not so necessary for our problem statement. The image got after filling the holes are represented by N5.

Algorithm:

The following shows the algorithm used for calculating the area of the defect by labelling each defect and then by taking into account the defects which have a pixel value greater than 250.

LABEL image N5(L=1 to n)

For L=1 to n;

     Calculate : area(L)=AREA N5(L);

End

TOT_AREA=[]

For L=1 to n;

If area(L)> 250;

     TOT_AREA=TOT_AREA+ area(L);

     Eslse

     TOT_AREA=TOT_AREA;

End

End

4.6. EVALUATION

The feature extracted from the NN output for decision making is the area of the defective region. The calculated area of the defective region is compared with the Expert area. Expert area of a defect is the best result produced and it is selected manually.

$$A_{IMG} = EXPER\_AREA(IMG) - TOT\_AREA(IMG)$$

A_IMG could be a negative or a positive value depends on the image classification if it is over or under classified. The Absolute value of *A_IMG* is taken and the value should be minimum.

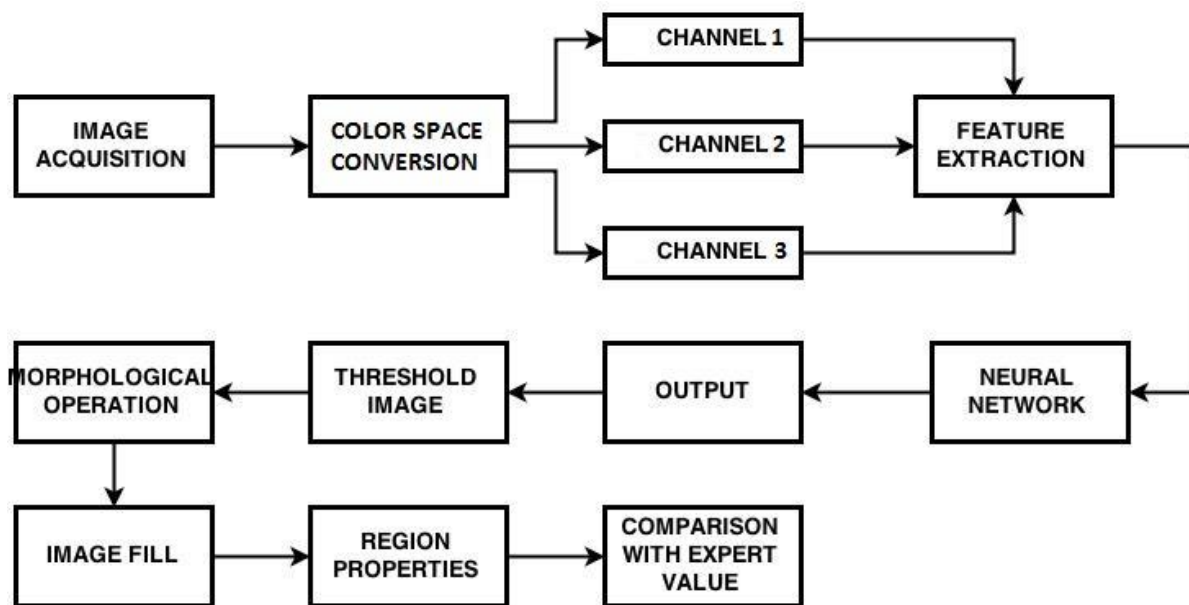The following fig.4.6 shows the block diagram of the algorithm applied.

Fig. 4.6. Block diagram of the algorithm

4.7. PROPOSED SYSTSTEM DESIGN AND COMPONENTS

The design of the system to provide effective solution for the visual inspection incorporating necessary sensors will be done. While designing the system there was several problems that was to be sorted out. Since the product of interest was like a cylindrical rod the choice of conveyor surface was a concern. Next was the choice for rejecting mechanism. This mechanism should be effective in terms of rejection time and efficiency. The presence of defect could be on any surface of the defect hence the positioning of the camera and the selection of conveyor material was important. The necessary sensors have to be selected to trigger the image acquisition and the rejection mechanism. The combined problems to be overcome is given below,

Problems to be considered for the design:

1. The design of the conveyor to support rolling objects.
2. Material of conveyor and position of sensors to capture image on all the sides of the defect.
3. Choosing appropriate Rejecting mechanism.
4. Selection of sensors.

4.7.1. Conveyor selection

The conveyor used for applications that uses small cylindrical objects like in pen and pencil manufacturing companies have a slightly different requirement. The conveyors used by them are chain conveyors that will hold the object in between the gap like in Fig.4.8 This type of handling cannot be used in our application since the defect could be in other side were the conveyor holds the stick marked in red curve which cannot be captured. The other conveyor is the conveyor with sliding planes Fig.4.7. this is used in pencil manufacturing companies where the pencil rests with the either ends resting on the planes. This cannot be applicable since the dowels are perfectly cylindrical and this may lead to rolling of it. The conveyor type we are proposing for our system is a special type with a transparent belt and small groves. This transparent belt is needed since we can capture the image of the stick even on the bottom surface. The transparent conveyor should have groves at regular intervals to hold the dowels in position. The Fig 4.8 shows the design of the conveyor proposed.
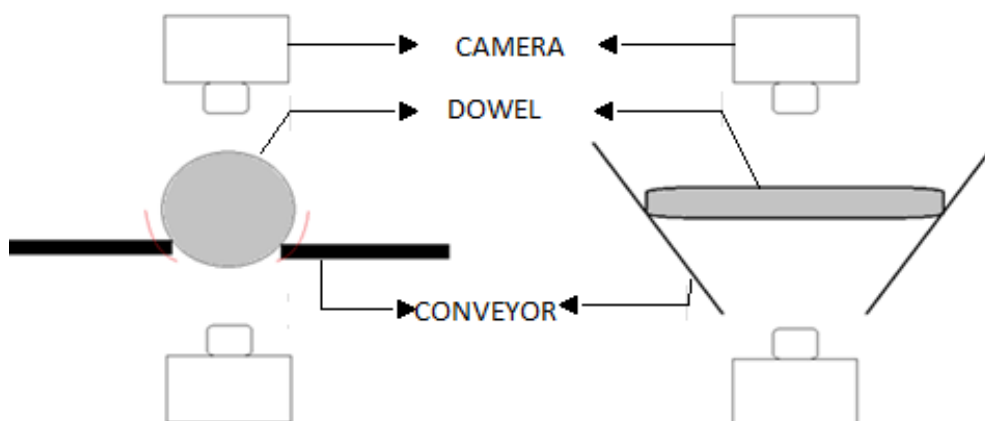

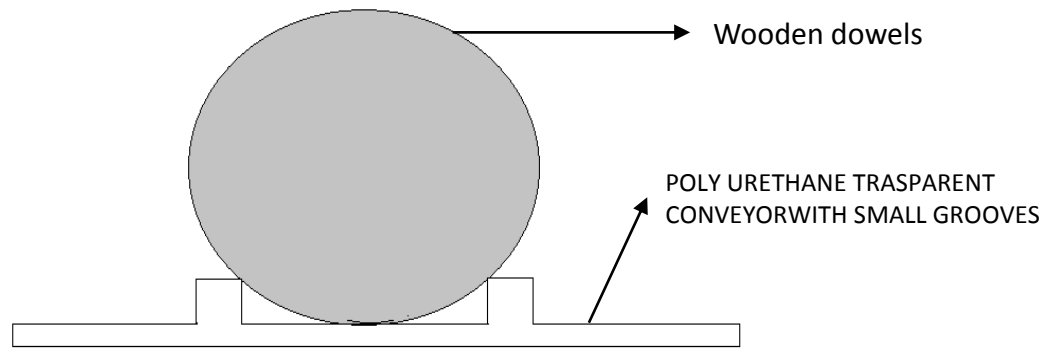**Fig. 4.7. Conveyor for placing the wooden dowels used currently in industries**

Fig. 4.8. Side view of conveyor proposed

The conveyor material for transparency will be Thermoplastic polyurethane (TPU) with a thickness of 1.10mm and weight 1050g per m^2. The Neveron conveyor manufactures have this kind of conveyor without the grooves 2PUR10/CW. The following Fig.4.9 shows the conveyor application and the transparent belt. The Fig.4.10 is the drawing of the proposed conveyor system which was drawn in Catia V5 design software for better understanding.

Fig. 4.9 Transparent conveyour systen for colour products [60] Transparent conveyor beltbelt [61]
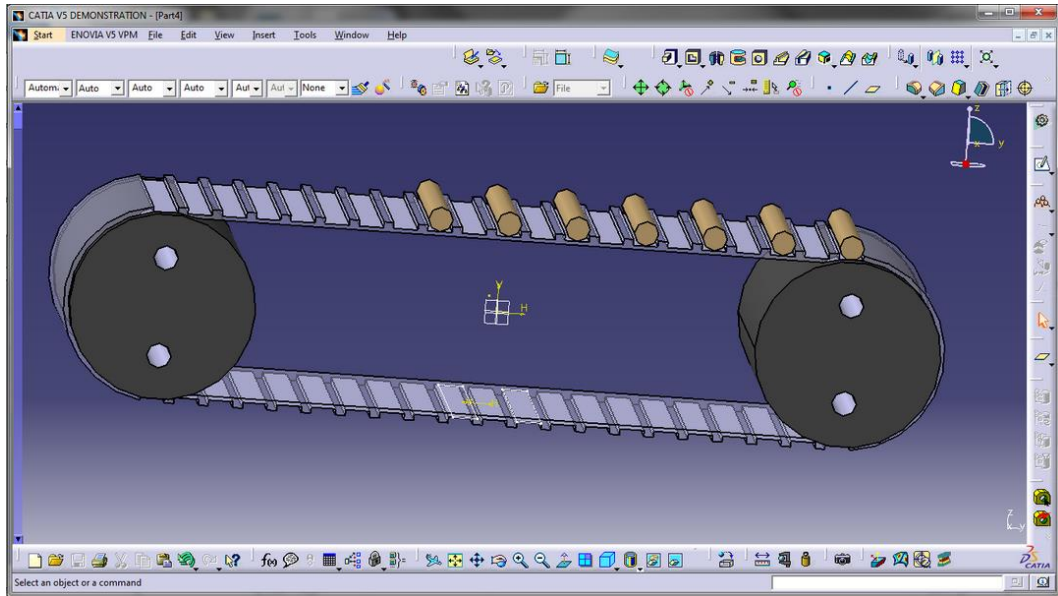
Fig. 4.10. Conveyor proposed drawn in Catia V5.

4.7.2. Camera selection and positioning

The camera is one important sensor for vison system. The camera selected for our system is a color one because we are going to process on the different color space of the image. The camera selected should have the following properties.

- High frame speed for fast image capture.
- Setting the focus of the lens according to need.

The vision camera In-Sight 7000 has all the features with additional flexible lighting of different colors. The Fig.4.11 shows the vision camera In-Sight 7000 for our system. The camera is positioned in two different places one to capture the top surface and other to capture the bottom surface. The top surface rejection is done first and then followed by rejection at the bottom side.

Fig. 4.11.The vision camera selected for our system [62]

4.7.3. Lighting selected and positioning

Lighting is needed when the image is to be captured since the processing is going to be in color image. The improper lighting can produce shadows and reflection. For our proposed system the lightings will be inbuilt in the selected vision camera.

4.7.4. Actuator selection and positioning

Based on the decision made by the computer software whether the stick is defective or non-defective the actuator should get signals from the controller to turn on or turn off the actuator. The actuating scheme used is a pneumatic solenoid value Fig.4.11 connected with a pressure pumps. When dowel is non-defective the solenoid valve is in normal position where there is no air flow. When the dowel is defective the controller sends signals to energize the solenoid valve and this position the air will blow the defective dowel. The actuator is placed next to the camera as shown in the Fig.4.13.

Fig.4.11 Pneumatic solenoid valve [63]

4.7.5. Through beam sensor

Through beam sensor is a type of photoelectric sensor. This is the most effective and reliable form of photosensing. The through beam sensor has two separate housing one for the transmittera nd the other for the receiver. The emitter produces the light and the receiver has the sensing element which will detect the presence of light. The receiver continuously receives light from the emitter when there is break in the path due to an object the receiver will send an electrical signal to the output. The positioning of the through beam sensor is shown in the following Fig.4.12. The Fig.4.13 is drawn in catia V5 a design software to show the system in 3D view.
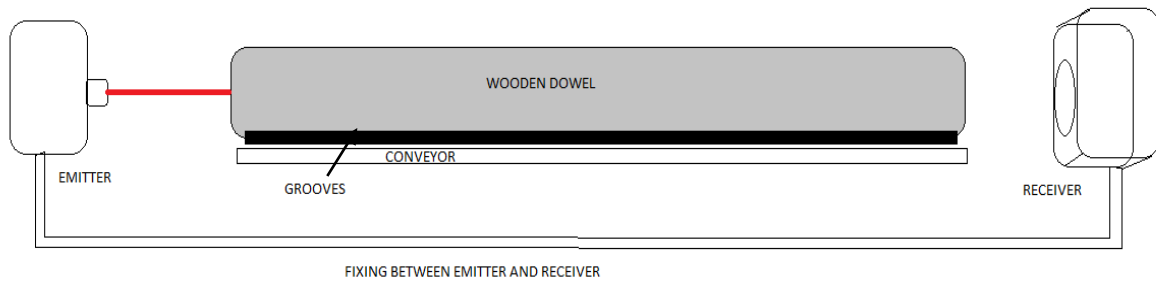
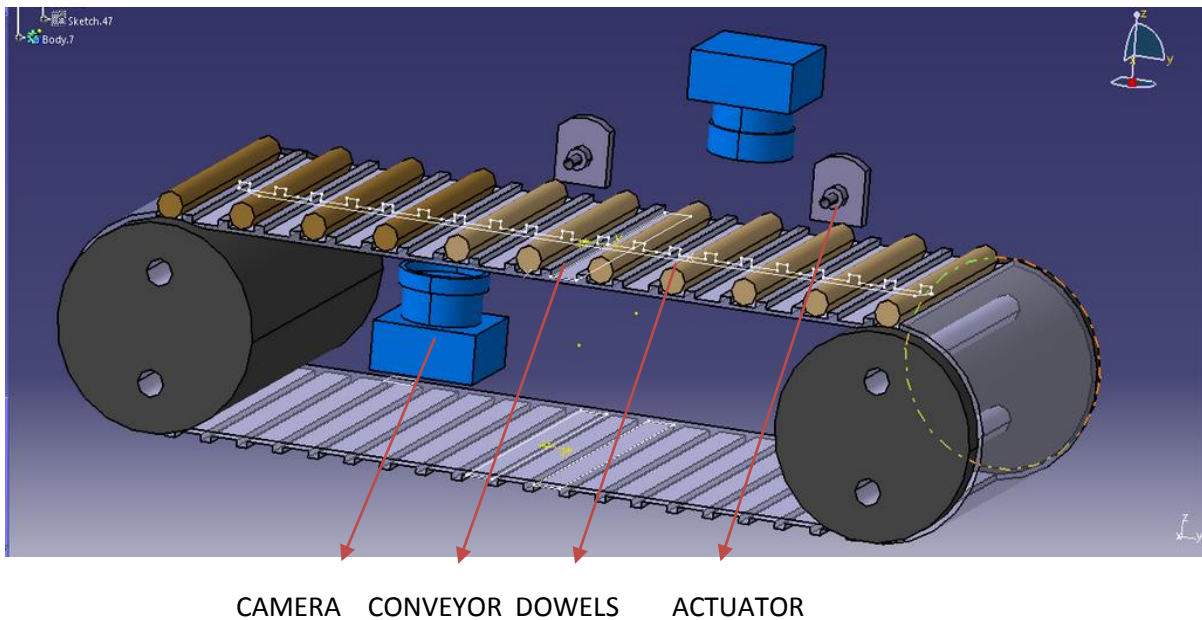**Fig4.12 Front view of the position of through beam sensor**

CAMERA   CONVEYOR DOWELS   ACTUATOR

Fig. 4.13 Basic design of proposed setup

4.7.6. Design of setup

The design of system for real time was proposed in the previous section. The components used in assembling the setup is shown in the following schematic diagram Fig.5.15 .The camera used for image acquisition is 8MP which has a capacity of 8GB and can click about 2006 photos. It has an operating voltage of 2.7V to 3.6V. The camera will generate a digital output and this output will be connected to the frame grabber board in the PC. The role

of the frame grabber is to transfer the image data directly to the PCI bus to the memory of the PC. For an 8 MP camera the picture is about 3264 pixels wide by 2448 high.
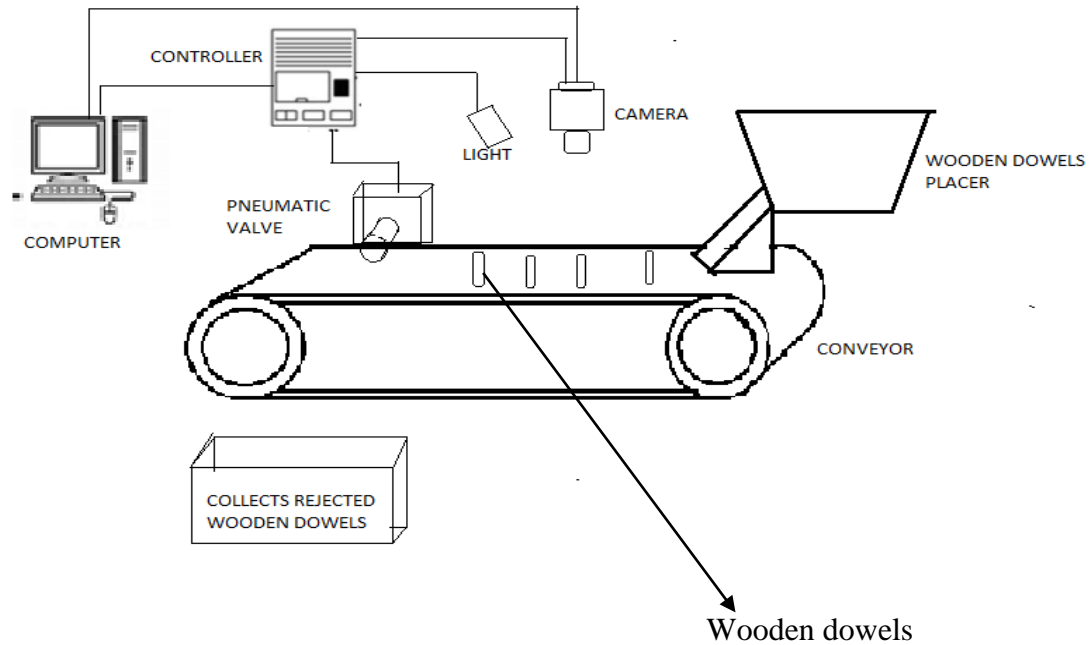

Fig. 4.15. Schematic of the setup assembled

The lighting unit is needed during capturing of the image. The lighting unit should be taken much care as improper lighting may worsen the defect detection and the algorithm developed will not prove good results. The shadow formation can be eliminated by placing the lighting in the perfect place. In our prototype setup we are using a flood light which has 230V, 50Hz operating frequency and has a maximum of 150W power. This flood light cannot be used for real time application as it produces a lot of heat. For this prototype system this flood light can be used.

The conveyor belt has to be moved according to the speed the image can be captured. The conveyor is attached with a servo motor and a Frequency converter. The power supply circuit used is the LPH-18-12 class 2 power supply it can produce an output of about +12V and 1.5A. The power source is given to the frequency converter which is used to control the speed and torque of the servo motor by varying the frequency and voltage.The pneumatic blower is used as actuator and it is connected with the pressure pumps. It will work based on the decision from the computer which runs the algorithm and provides accepted or rejected signals.This

system in Fig. 4.16 is at Kaunas university of technology faculty of electrical and electronics engineering, Lithuania under professor VidasRaudounis.
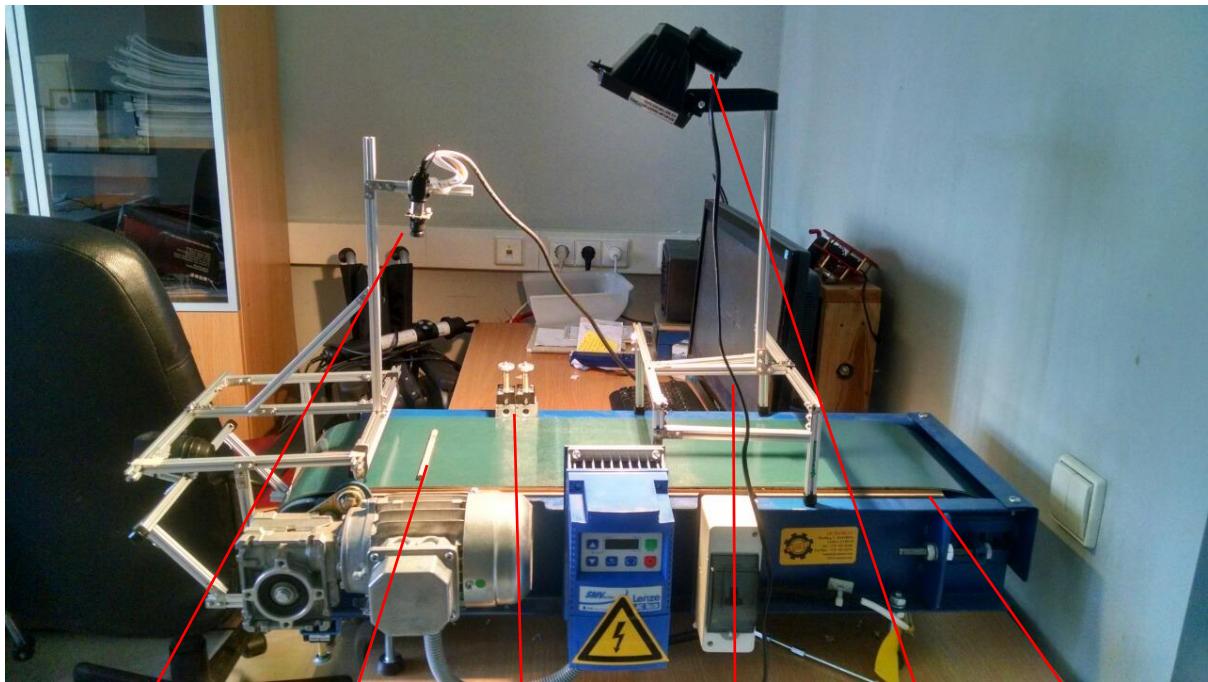
Camera   Wo1oden stick   Pneumatic blower   Computer   Lighting   Conveyor

Fig. 4.16. Set up of the automatic visual inspection system (at Kaunas university of technology faculty of electrical and electronics engineering, Lithuania, under professor VidasRaudounis)

The proposal of the system was made and the design of the optimal type of conveyor that will be needed for handling the dowels was given. The selection and positioning of the sensors and actuators which is also an important task was suggested and the setup was constructed.

5. EXPERIMENTAL INVESTIGATIONS

5.1. EVALUATION OF NETWORK STRUCTURE AND SLIDING WINDOW MECHANISM

While designing and evaluating the algorithm the effective selection of the network structure in terms of training time and accuracy was studies and then the effective way of extracting the features was also investigated.For extracting the features a sliding window mechanism is used there are two ways which will be effective for sliding window technique for mean calculation are.

1) NL filtering.
2) Column filtering.

The NL filter and Column filter are inbuilt functions in MATLAB. The best sliding window technique is selected based on the time needed for processing and the results produced. In both the cases Column filtering was proved to be effective since it needed approx.10 times less time as needed by NL filtering the following Fig.5.1. shows the comparison. And even there was error in the reconstructed image by NL filtering and this is because of the padding done by NL filter for the corner pixels.

TIME COMPARISON NL AND COLUMN FILTERING

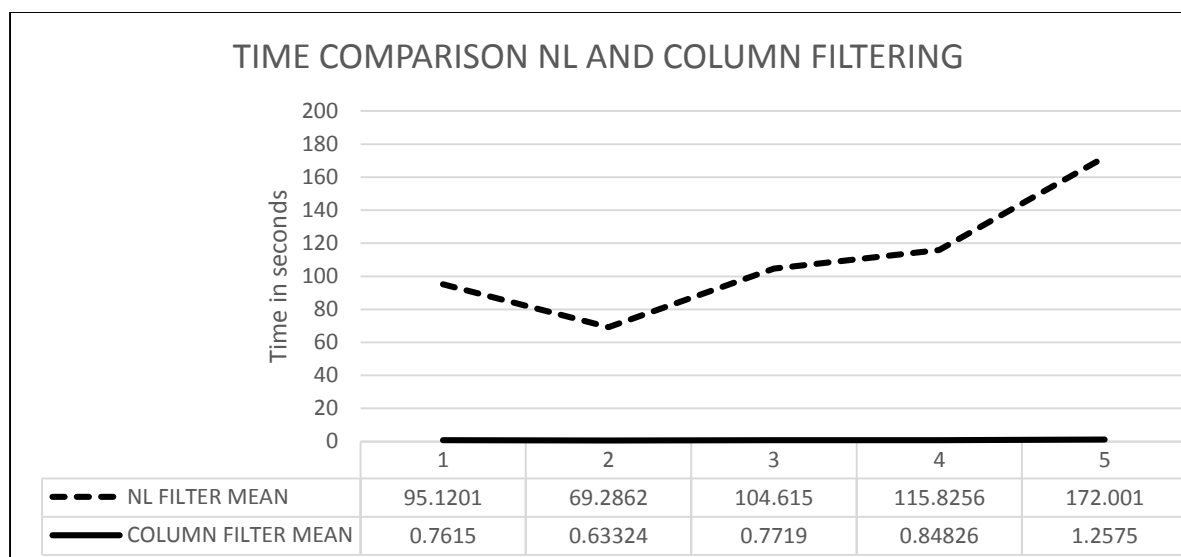|	1	2	3	4	5
NL FILTER MEAN	95.1201	69.2862	104.615	115.8256	172.001
COLUMN FILTER MEAN	0.7615	0.63324	0.7719	0.84826	1.2575

Time in seconds

Fig. 5.1. Time for execution NL filtering and column filtering.

Between selecting the best way to extract the features the next step will be to select the best network structure to find the defect. In [64] it has been studies for the face recognition system the best neural network structure would be the Pattern network and when it is trained with Levenberg Marquardt training algorithm and the results were verified with the Mean square error, number of iterations and recognition rate. And the cascade forward network works satisfactory with LVQ method as training and pattern net has a very bad performance with LVQ so this training method is not going to be used of its poor performance. [65]Hence for our system we will take Cascade forward network and the pattern network to test which will prove better results. The training algorithm used will be Levenberg Marquardt training algorithm for cascade forward network and scaled conjugate gradient for pattern network structure. The following Fig.5.2, Fig.5.3 shows the effective classification between the two different network structures for different number of neurons and the time in seconds taken for training.

From the following fig 6.2 and 6.3 it is inferred that the CFN structure needs very much time for training which cannot be the case when it is going to be used real time, this time consumption is due to various problems mentioned in[66] like the step size problem. And even in finding the amount of defect patternnet worked well as it is well defined for identifying patterns and it had a minimum deviation than CFN.
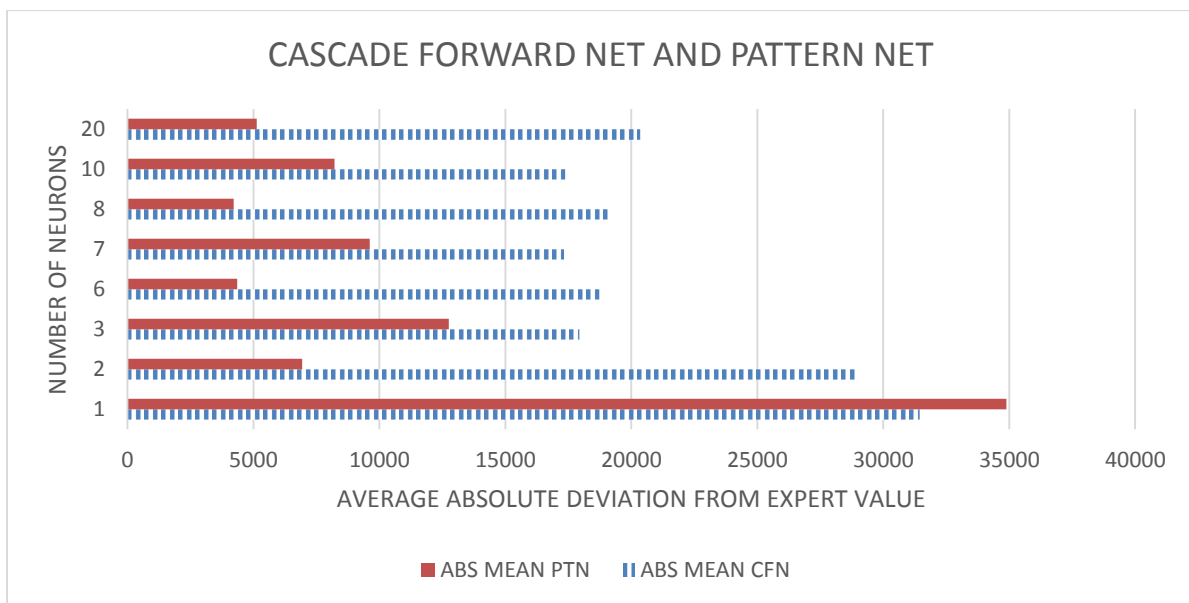

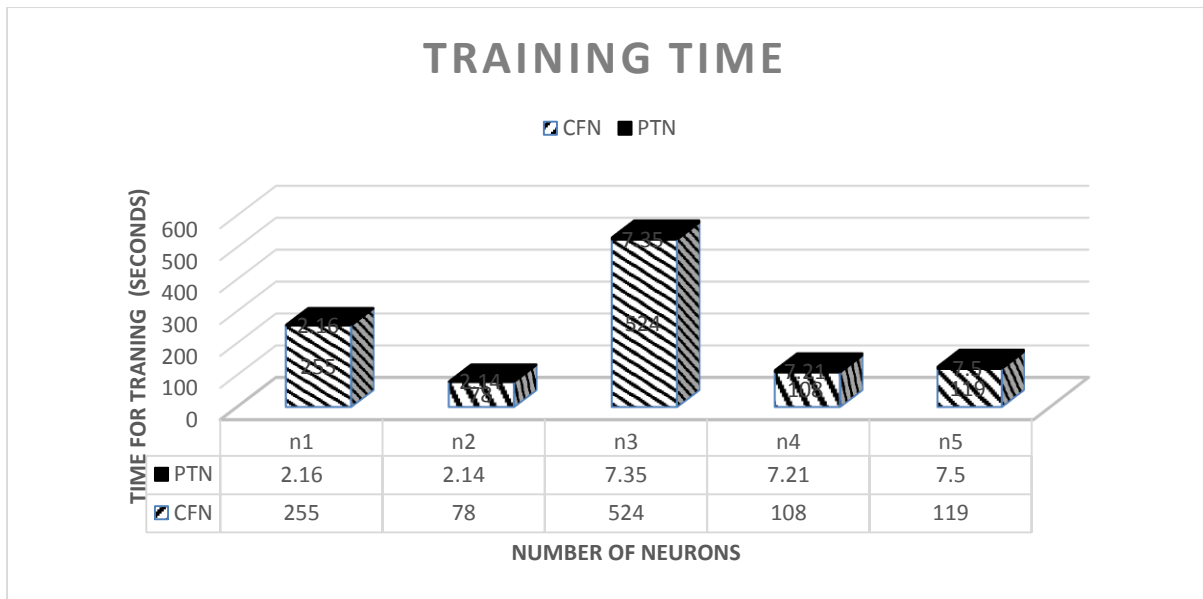**Fig. 5.2. Performance of Cascade forward net and Pattern net structure**

Fig. 5.3. Training time for cascade forward net and patter net

It is seen that the performance of the Patternet structure was better and wiser with all positives. The cascade forward net structure was too much for our system and it leads to poor results due to its continuous learning. The sufficient and effective NN structure was identified. The column filtering was found to be effective.

5.2. EVALUATION OF EFFECTIVE COLOR SPACE FOR DEFECT DETECTION IN WOOD

The defect detection scheme used so far for wood defect segregation was mainly based on the grey scale images. Processing and defect detection based on the Grayscale-based features of GLCM(Grey level co-occurrence matrix) such as Contrast, Energy, Entropy Correction was suggested by [67] Other methods by [68][69] works on grey scale images.The neuro fuzzy based defect detection [70] used the R G B color scheme for defect detection. There has been good amount of literature on using one color space for selecting different features for classifying different type of defects [71].

In this section we will evaluate the color space that will provide good defect detection and even to check the performance of combination of the bestcolor space with just one feature extracted. The color feature that are generally extracted from an image is the pixel value of the image. The pixel values of an image is distinct it cannot provide much effective classification. The other color features that are generally used are the mean, Standard deviation and skweness

call the color moments. The feature which will directly relate to the color value is the mean value of the pixels. The features were chosen to be simple so there could be better understanding between the different color spaces they are the mean and the 9 neighbouring pixels represented as C.

The different color space image we will be working are

1) RGB IMAGE
2) RGB CONTRAST ADJUSTED IMAGE
3) HSV IMAGE
4) LAB IMAGE
5) YIQ IMAGE
6) YCbCr IMAGE
7) XYZ IMAGE

The area of the defect is calculated for every wooden dowel taken for the study and the results produced after post processing for each and every color space was analysed. This process was done even by varying the number of neurons in the hidden layer to analyse the effective network structure. The graphs shown for each color space will show the variation of the calculated area with the expert area for each dowel in different number of neurons. The expert area is the area which is found to be in good match with the original defect.

The following Fig 5.4.a) are for RGB colour space shows the difference in expert are to obtained area for different images in the database for 1 to 10 neurons when mean value is input. Fig.5.4 b) shows the absolute average of the difference in the expert area to the obtained area when 9 neighbouring pixels values as given as input. The deviation of the area from the expert value should be minimum to have an effective detection.

The comparison graph between the mean and the C9 values says that the both the classification provided almost the same amount of classification with a little changes. In [68]Cavalin shows the comparison for normal grey scale image and RGB image and the percentage of accuracy was good for color image. The RGB image was able to find a good and distinct variation in the pixel values of the defective, non-defective and background regions which was easy for the NN to understand and train.
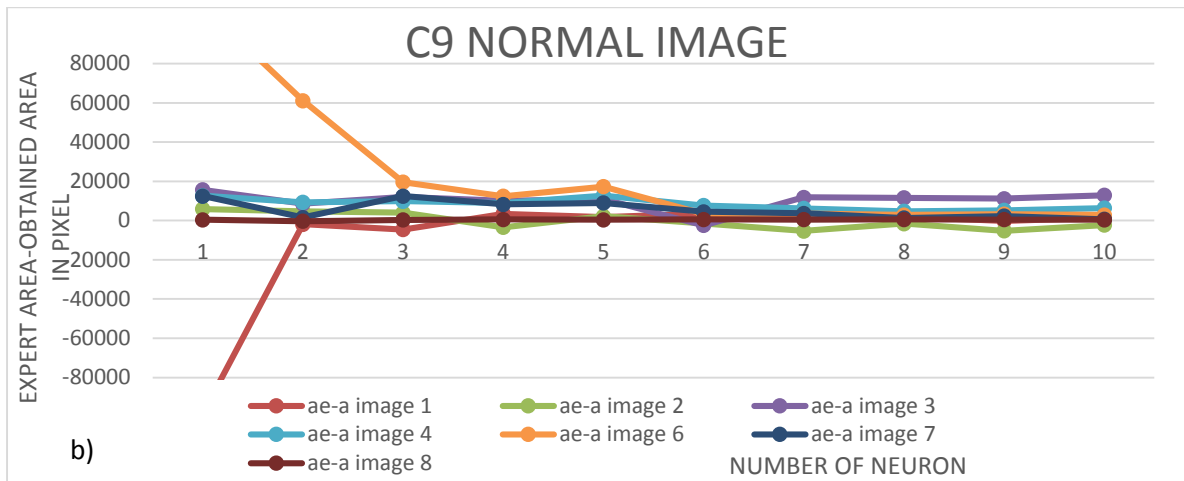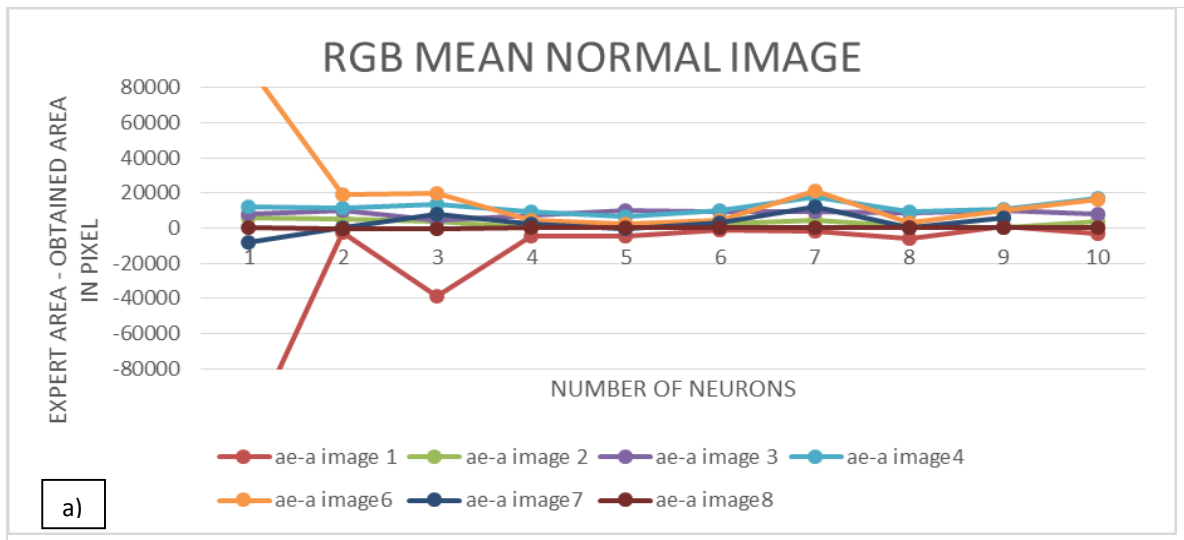
Fig. 5.4. Deviation from the expert value in RGB color space for different number of neurons a) for Mean input b) for C9 input

The contrast of the image was enhanced to find the comparison results of normal and contrast adjusted image. The contrast adjustment was done on the basics on the normal visual selection. The contrast adjusted image produced visually attractive image but the result of classification was found not as effective as the normal image. This is because when the image intensity is varied the pixel tends to lose its values and spans the histogram. The results of contrast adjusted image as input to neural network for mean and C9 data are shown in the following Fig.5.5 a) and Fig.5.5 b)
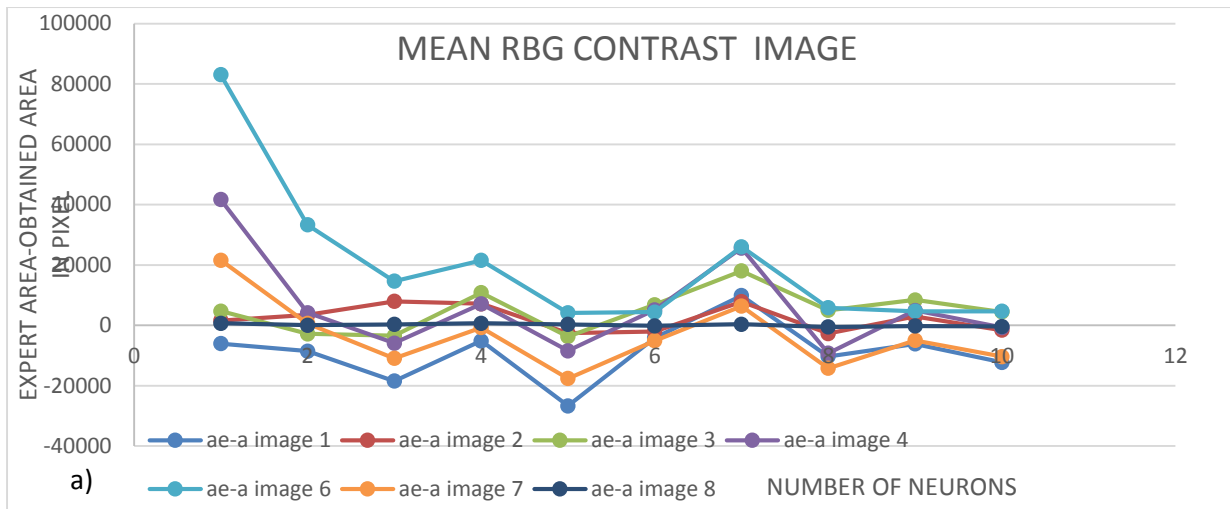
Fig. 5.5. a) Deviation from the expert value in RGB colorspace(contrast adjusted image) for different number of neurons.
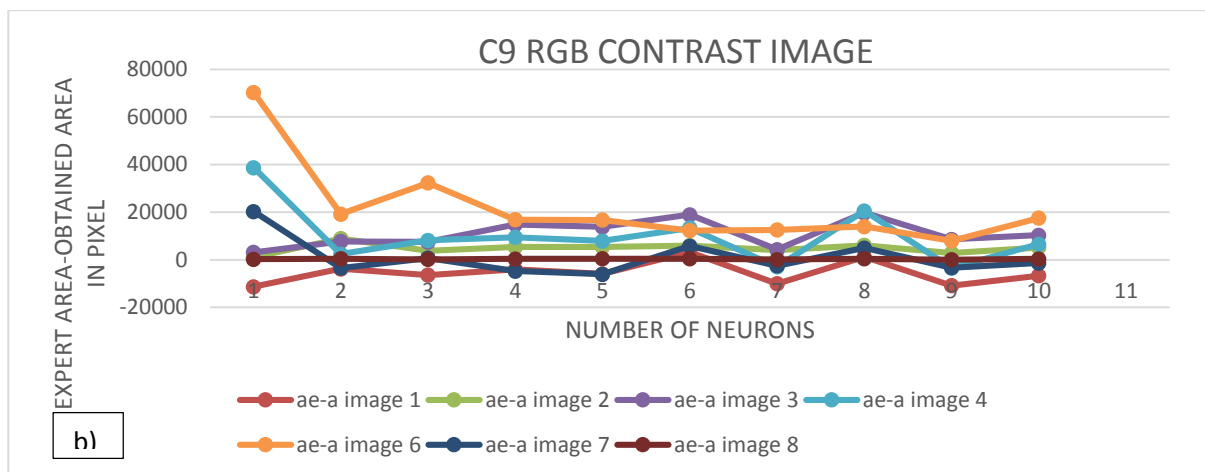

Fig. 5.5. b) Deviation from the expert value in RGB color space(contrast adjusted image) for different number of neurons.

From the Fig.5.5 it is inferred that the results produced were good for certain images and was bad for certain images. The curve ae-a for image 6 showed much deviation from the original defect and it was under classification. This means that the contrast adjusted image when given as inputs it was not able to fully identify the defect in image 6. This was due to the fact when the image was contrast adjusted the red pixels with a certain range of values in the mid-way to the white region were shifted more towards the white region. The other results were moderately good but it was not as accurate as the normal pic RGB. The color adjustment proved very much difference when it is measured in terms of pixel value.

The image was converted from RGB to L*a*b space and the individual L, a and b were processed and the neural network was trained.

Fig. 5.6. Deviation from the expert value in LAB color space for different number of neurons. a) Mean value b)C9 value.

From the results in Fig.6.6. it is inferred that the area found varies from the original area on an average of 25,000 pixels which is not a bad result but even it is not the best result. When analysing the reason behind this deviation the Luminance component is like a grey scale image which shows the effect on the lightness. The defect can be segregated to an extent with this 'L' parameter. In the remaining 'a' and 'b' the 'b' says the color balance between blue and yellow and the color balance between green and cyan. In 'a' it is easy to detect the defect since the defect had a good amount of red and yellow and the background is pure green. When identifying the defect the 'a' and the 'b' component shares a common color between the

45

defective area and the bad region ie the red and the yellow color. When these values are given to the neural network it confuses to identify the defect which is more closed like the non-defected region. This is the reason why the defect is not very well defined in this color space.

The next color space analysed was the HSV space. The image was converted and split into individual channel and the results were shown in Fig. 5.7 for different neuron numbers and different images.
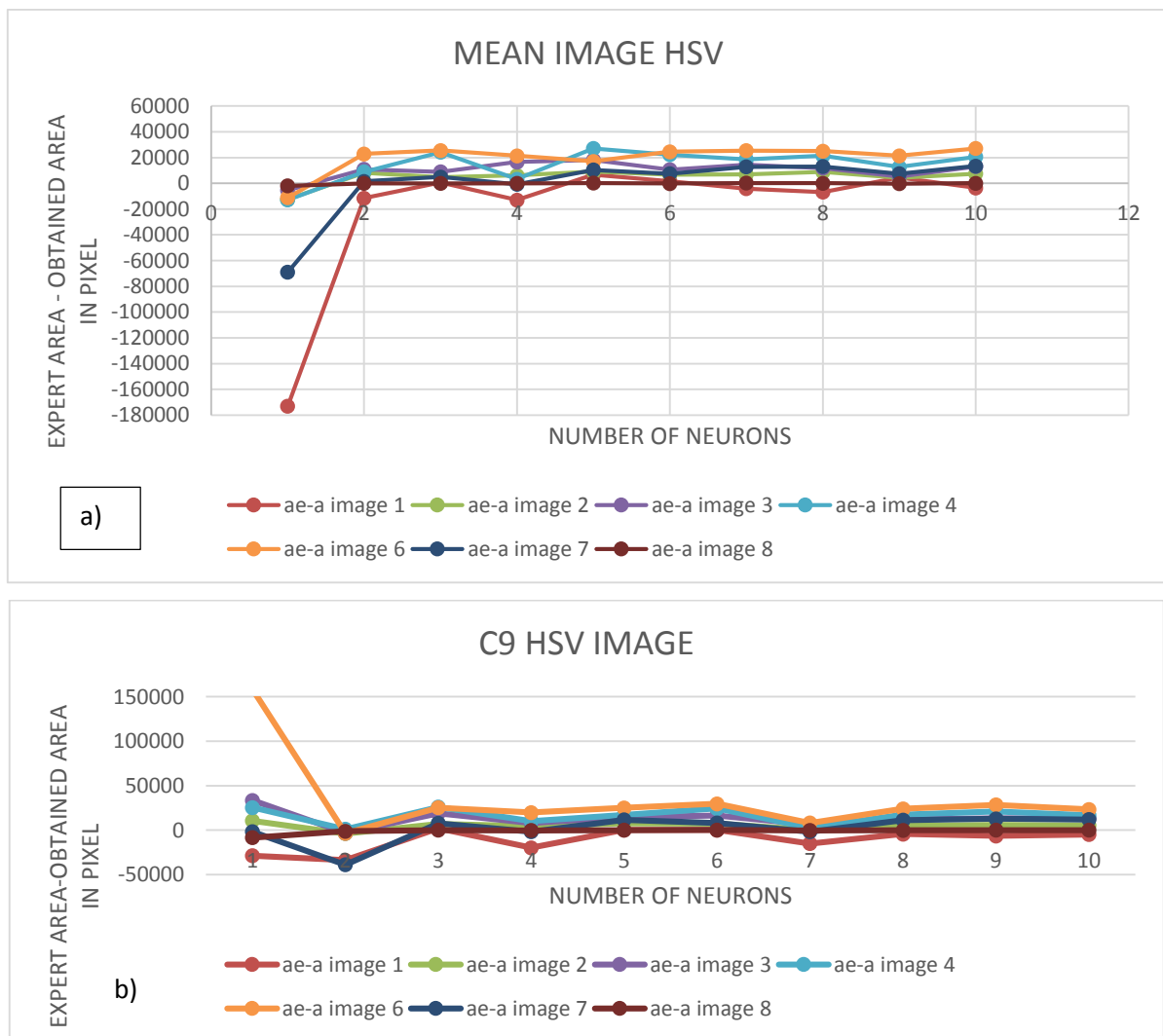

Fig. 6.7. Deviation from the expert value in HSV color space for different number of neurons.a) Mean input b) C9 input.

From these above graphs it is inferred that the HSV color space works well when there is high value of Hue for the defect. The ae-a of image 6 shows that there is much deviation from the

other image since it suffers from a low value of hue with the defect. When the NN finds low Hue value it misclassifies it as non-defective pixel.

The YCbCr colour space was also analysed by converting the original RGB image into YCbCr components and the results are shown below in Fig. 5.8.

Fig. 5.8. Deviation from the expert value in YC$_b$C$_r$color space for different number of neurons. a) Mean input b) C9 input

The results from the above graphs shows that the deviation on an average is less than 20000 pixels which is very good. This could be because the main pixels in the defect the red and the yellow are very well separated from each other as Cb which has yellow and Cr which

has the red Chroma. There are a little ups for certain neuron number and this is not the reaction of the color space in defect detection it is due to effect of number of neurons selected. The next was the YIQ image conversion and the following Fig 5.9 shows the results produced by them.

Fig. 5.9. Deviation from the expert value in YIQ color space for different number of neurons. a) Mean input b)C9 input

It is inferred that the YIQ space has a better performance than the HSV in identifying the defect. This color space was found to be very effective in skin colour identification in face detection but it did produce good results for certain image and failed for the other. The next and the last was the XYZ color space and the results was shown in Fig. 5.10 for the different inputs.

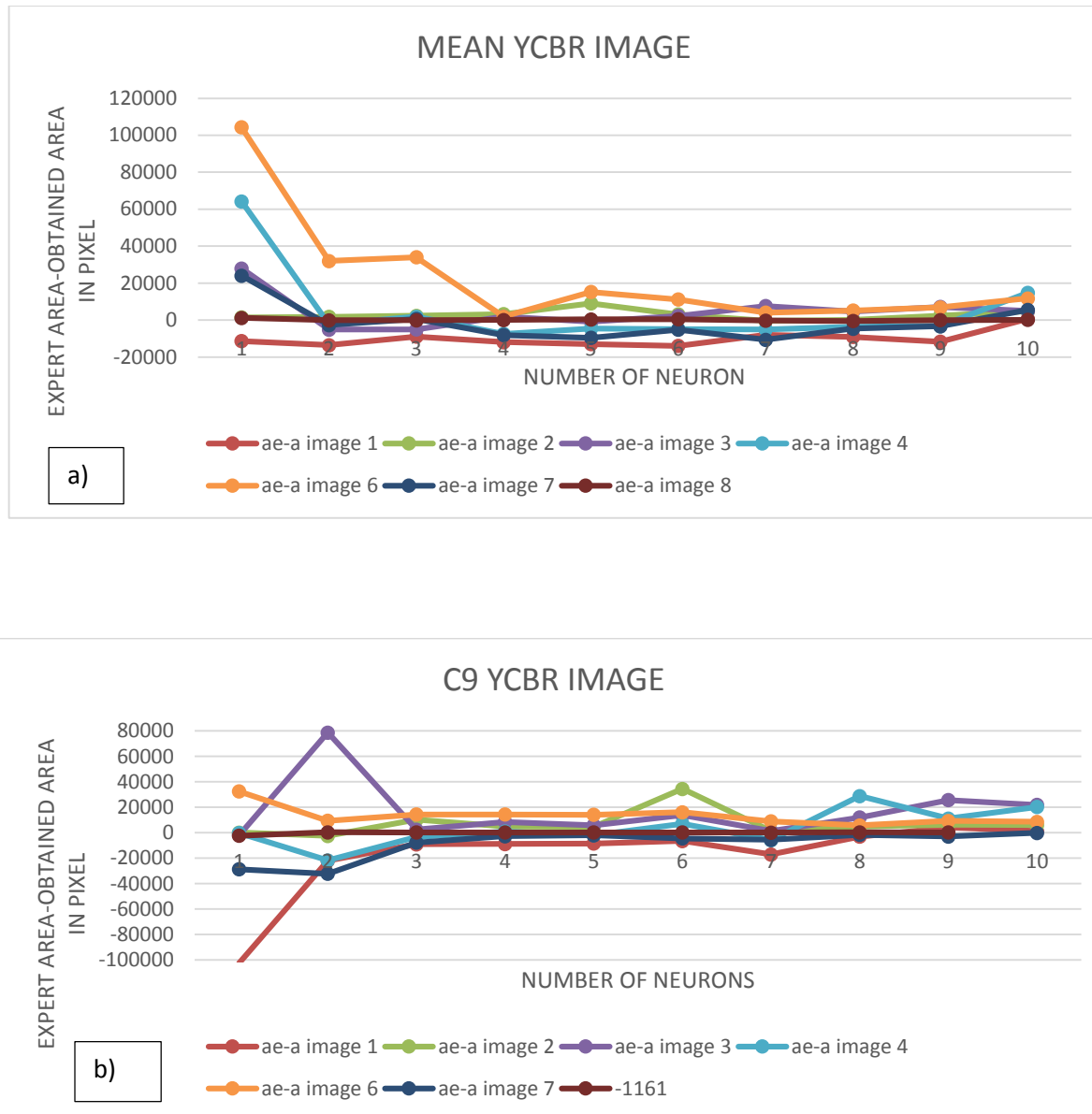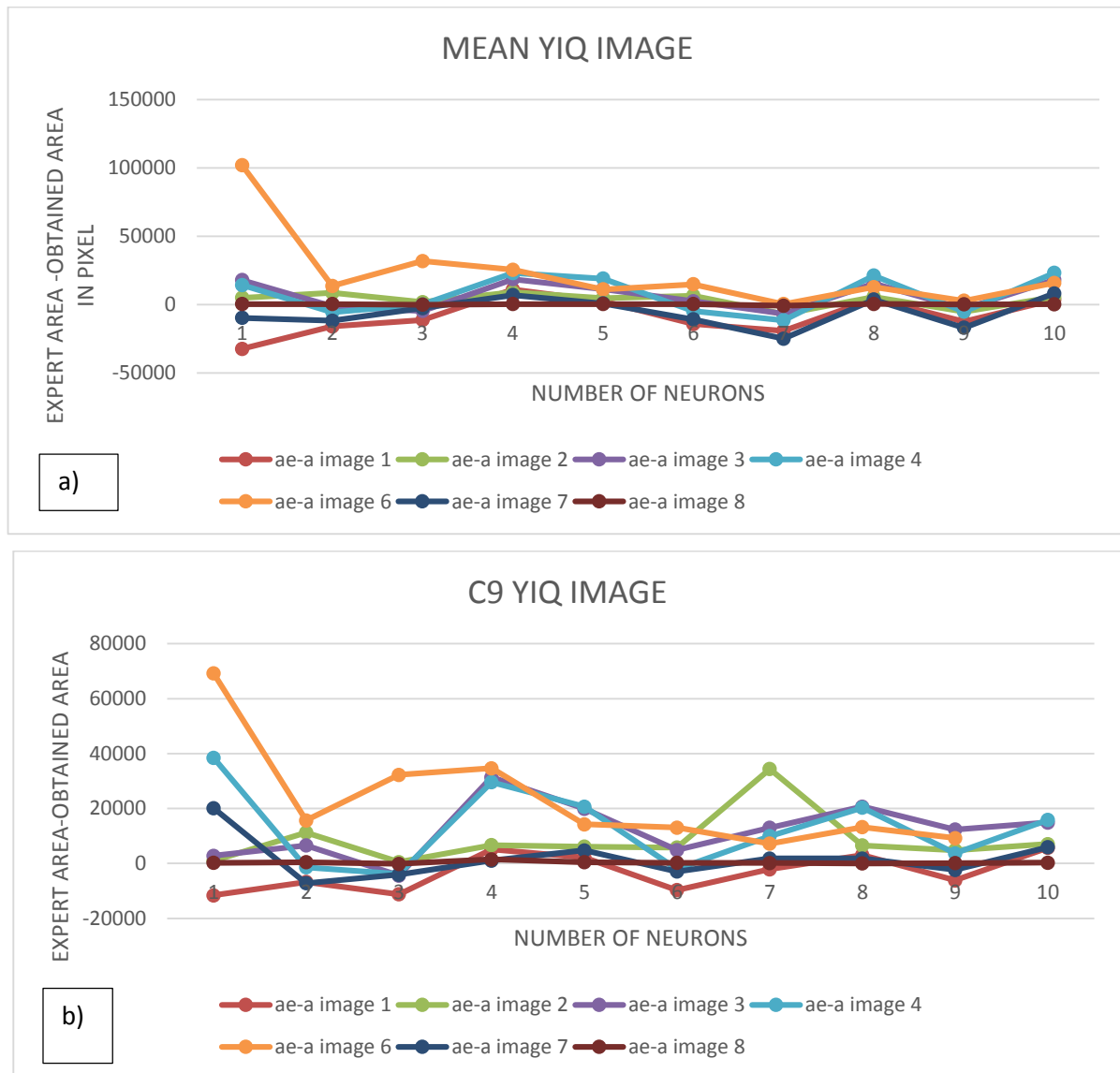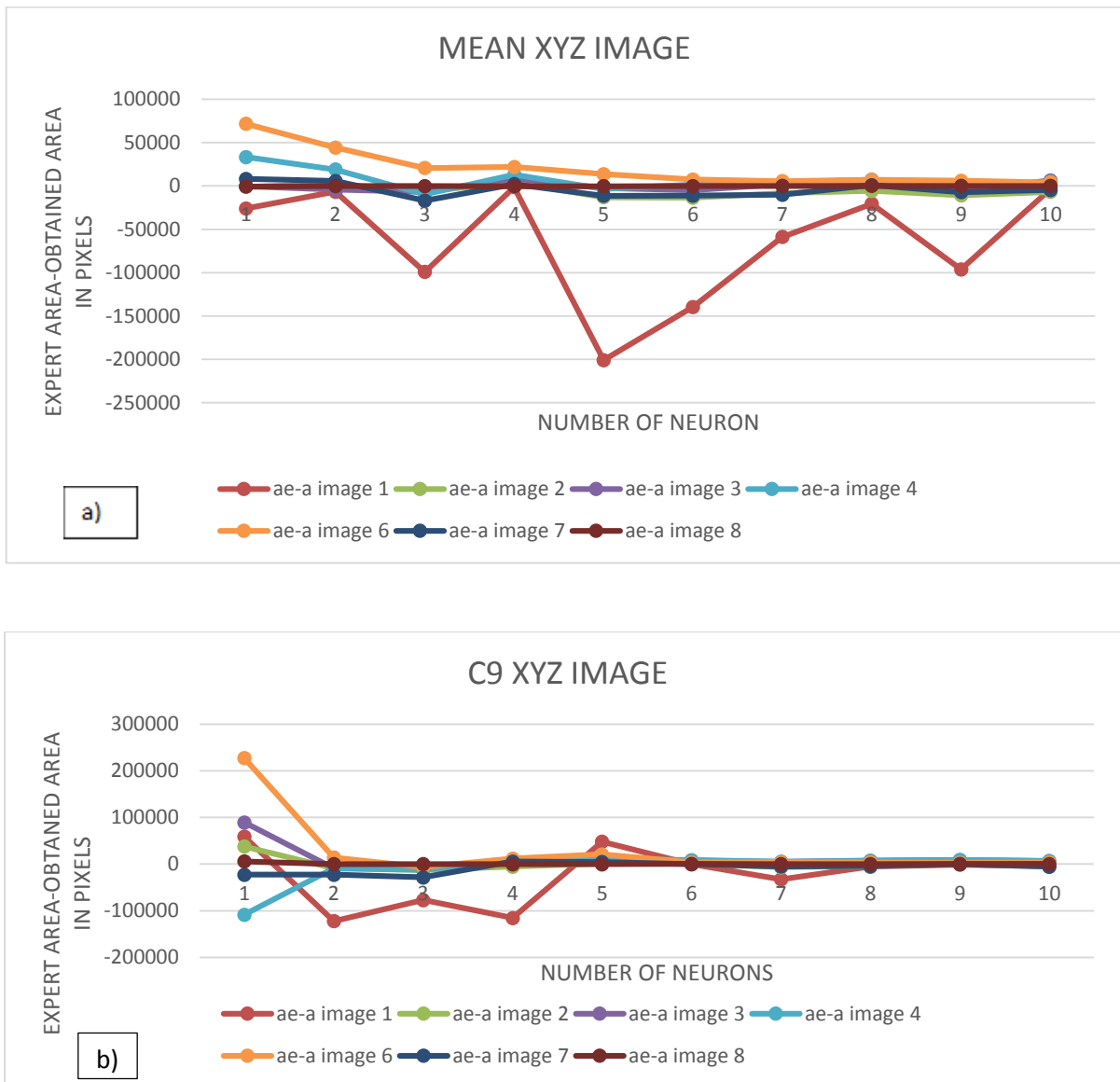**Fig. 5.10.Deviation from the expert value in XYZ color space for different number of neurons a) Mean input b) C9 input**

The results from XYZ was very good for 90% of image and failed very bad for other even for different neuron number. Y represents the luminance information, Z is quasi equal to blue stimuli and X is linear combination of cone response curve. This representation could not provide a much information on the values representation to the NN as the X is like a linear curve. When the image curve range is close to the trained database the defect was very well segregated. The neural network cannot understand the equation of the X curve and it reacts odd

when the X value was not close to the database. The NN cannot predict the value of the X curve with just the trained database of samples. If there was some other form of training to the NN about the X curve the NN could give perfect values for all the image. Since the focus of thesis will be on finding the effective colour space with simple features the XYZ color space was not suited without any additional complex manipulations.

The normal RGB color space produced results with a not much variation and the results were found to be consistent with all the images used for the study. Since this is the original color perceived by the camera the results were very good compared to the other space. The contrast adjusted image produced results with a max of 50,000 pixel difference for certain image which is also not a bad result but it was not satisfactory as the normal image. The LAB and the HSV color space produced results much similar. In [72] It is said that the HSV color space was more efficient that RGB color space but studies in [73] were contradictory were they found no notable change when there is a change in color space. The results produced by the experiments by me shows that there is some changes in HSV model when they are transformed from RGB space as some images did not produced results as expected. These previous studies shows that HSV space is much more effective for image tracking were shadows plays a vital role. Since the system used will have a good amount of lighting to avoid shadows the saturation and value component of HSV does not have a much part to play resulting in not so accurate defect detection.The LAB space being a device independent space was also facing the same problems like HSV but in a mild way.When you exactly want to match colors in different devices this space is much effective for processing of defects in wood it is not so necessery to work with high value color space. YCbCr space has the luma component , the chrom blue and chrome red sepated. The defect in wood will have a good amount of red component and this made a very good seggregation of the defective region. The results produced were much better that the HSV LAB and the contrats image. The ntsc space called the YIQ color space is has luminance in the Y and I has orange and cyan information and Q the green hue information. This hue information was not so effective to detect defects which has good amount of red in its defective area.

All the color space could identify the presence of defect in the stick well and good but for detecting the efficient color space the LAB, HSV and YIQ failed much more in terms of effectiveness. The best working color space was found to be RGB and the YCbCr space. It is to be remembered that as Brunner stated in [74] that RGB is the original color space and the

rest of the color space have been derived from transforming the base RGB space mathematically. Hence when there is transformation it always could be prone to errors.

5.3 EFFECT OF NUMBER OF HIDDEN UNITS

The efficient design of neural network is decided by the proper selection of neurons used in the hidden layer. One important problem is to know the number of hidden neurons. When the number of hidden neurons is less than the requirement the network cannot be powerful. When the number of neurons is more than that required it results in a problem called the over training. So selecting the number of neuron is important for a given problem. There have been many attempts to find the perfect number of neurons which will make an efficient system, but it will also depend of the type of classification or input data given. There is no way to find the perfect number of hidden neuron for our system to have good defect detection since most of the defect detection methods are based on segmentation, fuzzy logic and SVM. Hence a trial an error approach of trying and testing for different neuron numbers was done [75].

From the graphs studied previously it is found that the absolute deviation in the area is minimum for certain number of neurons and it is maximum for certain neuron number. It also slightly varies from each color space. On the whole the performance was not good for 1 and 2 hidden neurons for all the color space. This is true as suggested by the rule of thumb mentioned in [76] the number of neurons should be between the number of input layer and the number of output layer. Very good performance are generally seen between 4, 5 and 6 neurons. This goes well with the other thumb rule stating that the number of neurons should be 2/3 size of the input layer plus size of the output layer ie 5 neurons exactly for mean. And it also satisfies the other rule of thumb which says that the number of neurons should be less than twice the output layer which is less than 6, and it shows good performance in the range of 4, 5 and 6 neurons. When the number of neuron is 1 it results to under fitting. When the results between mean and the 9 neighbour c9 are compared for different number of neurons it is found as the number of neuron increases the performance is good with C9 values while the performance for mean is good when the number of neurons is less. This is because when c9 is given as input the inputs are 27 so when the number of neurons is less as said in rule of thumb the performance of NN becomes less. For mean the number of inputs are 3 and it gives good results for less number of neurons

in the hidden layer. The consolidated graphs shown in fig. gives better understanding of NN behaviour for inputs.

The effective number of hidden units is found to be dependent on the number of inputs. When the number of inputs is 3 the number of hidden units needed was between 4 and 6 but when the number of inputs is 27 we found good results when the number of hidden units is more. So it is concluded that the selection of the best number of hidden units decides the accuracy which also depends on the number of inputs.

5.4. SELECTION OF BEST COLOR SPACE AND NEURON NUMBER

The previous section overview all the color space separately and their reaction to the number of neurons for two different input. The following Fig 5.11 shows the consolidated graph which shows that the normal RGB image features and the YCbCr image feature produced the best results in both the cases and not to leave the XYZ space which produced excellent results for 90% of image and very bad results for the 10% of image. The fig 5.12.shows how the input image will look when it is converted into diffrent color spaces. From the graphs it is concluded that the RGB and YCbCr space works well in defect identification.
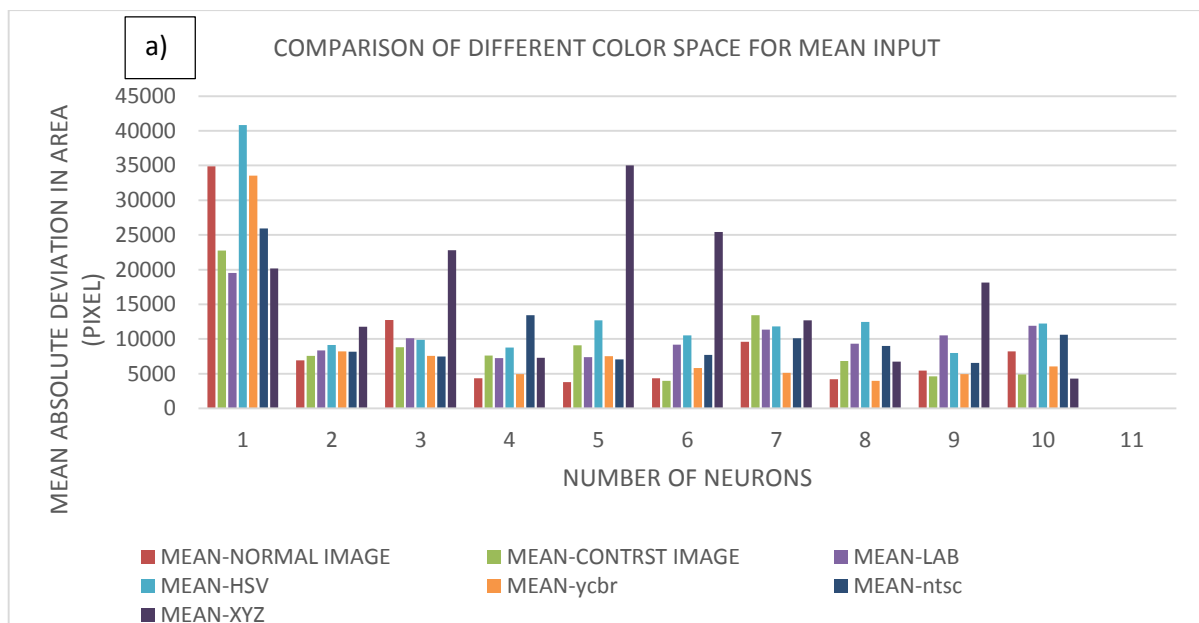
Fig. 6.11. The comparison of performance in all studied colour space a) Mean input
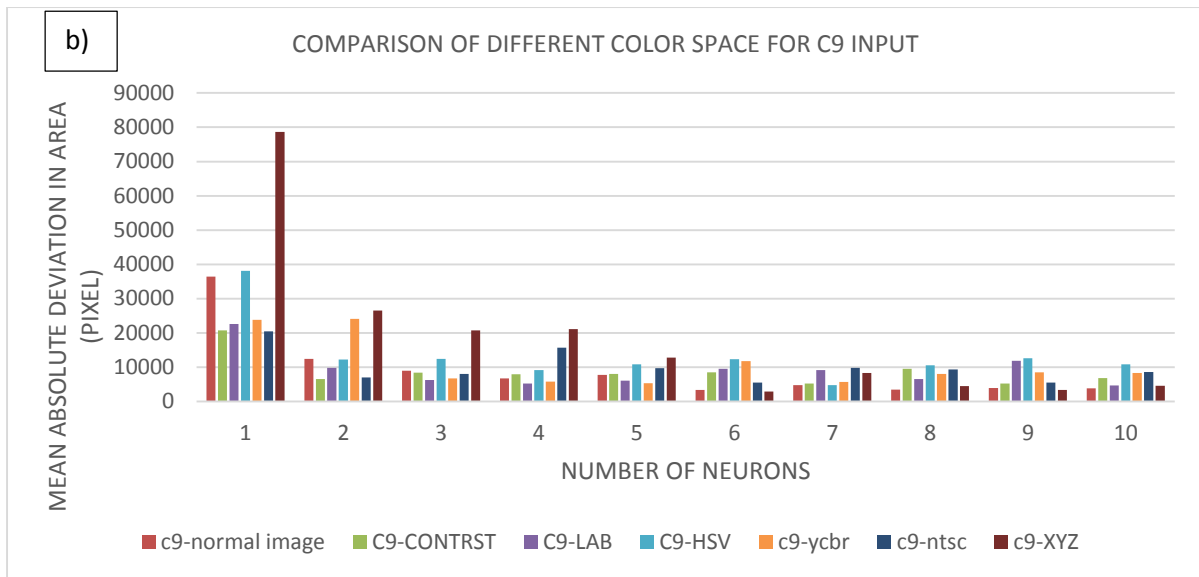
Fig. 5.11. The comparison of performance in all studied colour space b) C9 input
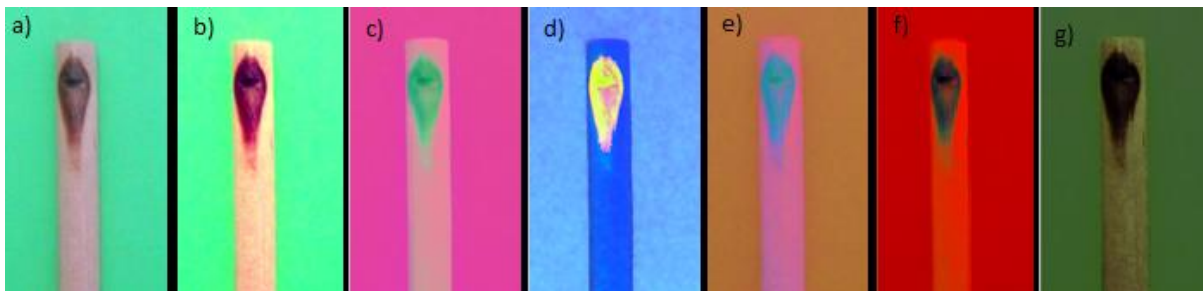
Fig. 5.12. Image in diffent color space a) RGB b)RGB contast adjusted c) L*a*b d) HSV e) YCbCr f) YIQ g) XYZ

The following Table. 5.1 will show the percentage of finding the area of the defect in all the colour space for the best and the worst neuron numbers according to the previous result for mean input. The percentage value goes above 100 in certain cases where there is extra neighbouring pixel which are calculated as defective area. The percentage value is very good if it is between 95-105%. The RGB and YCbCr shows the best value for percentage of defect found between shown in the shaded box for 4,5 and 6 neuron number. And it is clear that since the number of inputs is 3 the neural network works well between the 4 and 6 neuron number.

Table. 5.1 percentage comparison of accuracy of different color space with the best and worst neuron numbers

	NEURON 1	NEURON 4	NEURON 5	NEURON 6	NEURON 10
RGB	101.46%	96.22%	96.916%	94.807%	90.6%
LAB	79.612%	98.68%	100.09%	95.602%	84.79%
HSV	152.01%	93.79%	83.787%	86.628%	85.66%
YCbCr	61.35%	100.55%	101.25%	102.27%	92.23%
YIQ	82.28%	90.97%	101.08%	112.77%	86.461%
XYZ	84.50%	91.24%	139.61%	129.09%	99.84%

5.5. COMBINING COLOR SPACE

From the above conclusions a combination of two best color space features were combined and given for classification. The two best color space chosen were the RGB and the YCbCrcolor space. The analysis of the good bad and the background region done in data base extraction section proved that the defect has a much of red and the background has pure green pixels. So it is effective enough to take the red and green pixels from the RGB image. From the YCbCr image the luminance component is neglected and the focus was on the Chroma of the red since the defect has a lot of red. The Chroma of the blue was also taken since the blue pixel from RGB image was neglected. The following graphs Fig. 5.13.shows the result of this algorithm. The result of RGCbCr looks like the mean of RGB and YCbCr lines. This takes the effort of The R and Cr component in finding the defect and the G component for segregating the background. The Fig. 5.13.b) shows that the RGCbCr results are much close to the expert value for different image than the individual RGB and YCbCr since its takes the effectiveness of both the color space into one and to proceed with the number of neurons needed for the neural network.

The range of Neurons between 5 and 10 seems to produce good results. This is due to the fact that the number of inputs for the neural network is 4 and when the number of neurons becomes less than the number of the input there occurs under fitting. The Table. 5.2 shows that the percentage of finding the exact area of defect. The combination of the two colour space produced the very best result of 98.4% and 99% accuracy for neuron number 9 and 10. The individual RGB and YCbCr had neurons between 4, 5 and 6 to be the best since the number of

54

inputs given for mean calculation was 3. The combined space had 4 inputs and it produced good results for neurons above 5. From this it is concluded that the combination of the colour space produced much better results and the effect of number of neurons in the neural network is very important in NN design.
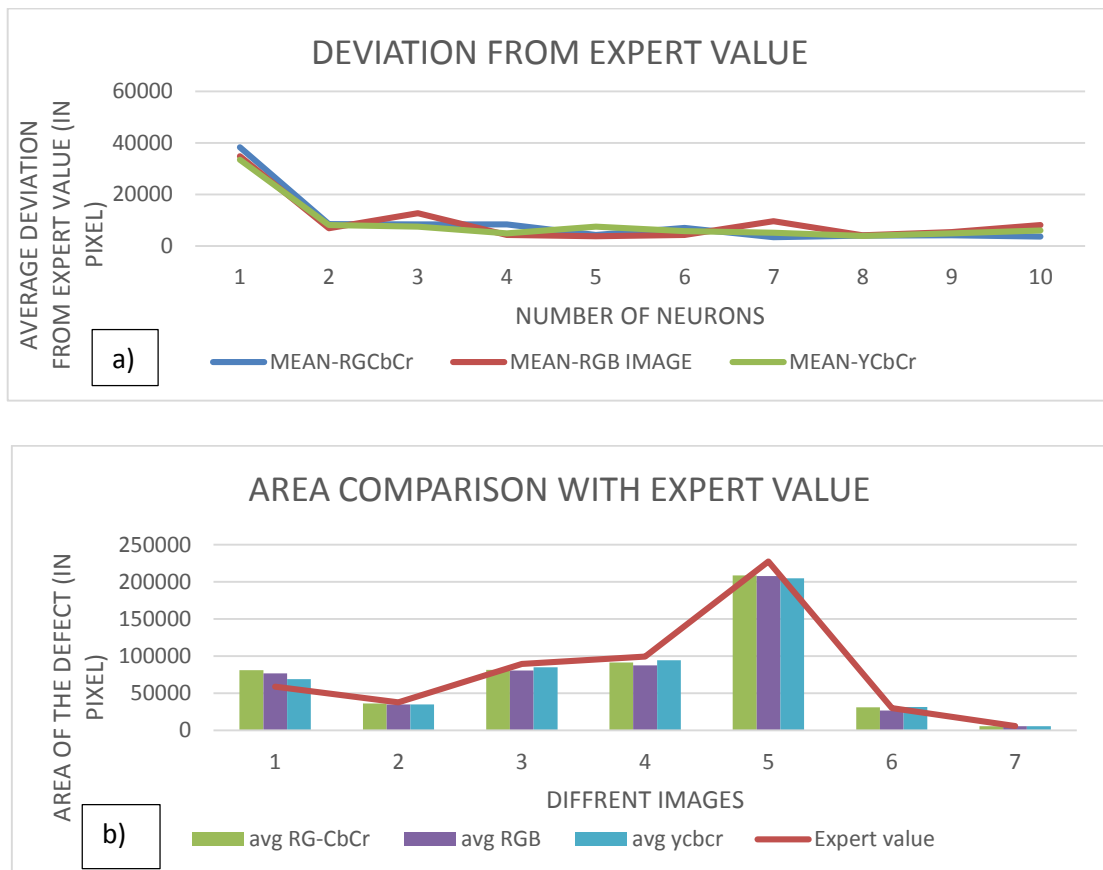
Fig. 5.13. Performance of RGCbCr space a) For different neuron numbers b) for different images.

Table. 5.2 percentage comparison of accuracy of combined color space with the best and worst neuron numbers

	NEURON 1	NEURON 4	NEURON 5	NEURON 6	NEURON 9	NEURON 10
RGB	101.46%	96.22%	96.916%	94.807%	92.6%	90.609
YCbCr	61.35%	100.55%	101.25%	102.27%	100.26	92.23%
RG-CbCr	113%	92.65%	95.211%	94.6%	98.4%	99%

When the two color space was combined the results looked like the average of the accuracy of two color space individually. And the number of hidden unit also varied. Thus it is found that combinig features from different colour space worked well in our defect detection scheme.

5.6. TIME FOR ALGORITHM EXECUTION

Care was taken when deciding the process and the network so that it would give the less execution time. When a system is implemented real time one important factor is to reduce the time for processing. The time graph for different execution task is shown in the Fig,6.14.As we see the maximum time is taken for generating the output and also it is seen as the size of the image is more the total time is more. So it is suggested to capture smaller section of the image rather than taking a whole big image.
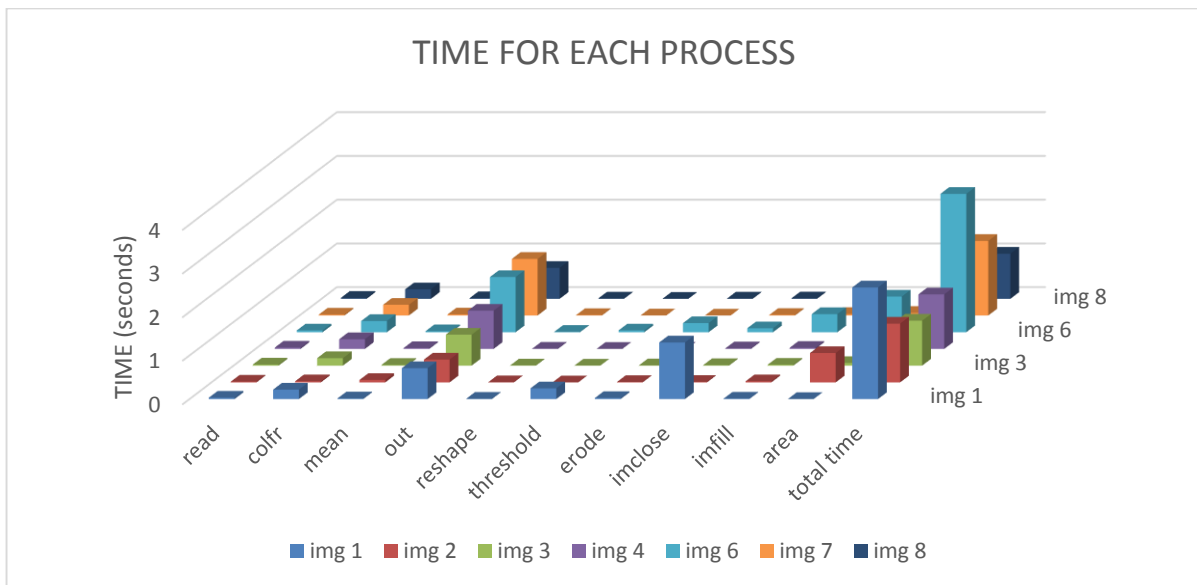

Fig. 5.14. Total time for algorithm execution

The time needed in seconds for processing was found to be good since the actuator section for rejection mechanism is placed at a distance with the image acquisition section. The time for execution of the task was found to be optimal.

6. CONCUSIONS

Automatic defect detection for wooden products have been previously studied and many sensor types and different algorithm for processing were proposed for identification of the defect. There was not so good understanding about the neural network classifier used for defect detection and what is the effect of color space in identifying the defect. And the reaction of a particular feature to different color space and to get the best combination of color space that could be used and to know if it much better in classification than using a single color space. From this an effective NN based defect detection scheme was developed and based on the results produced the following conclusions were made.

1. All the color space were able to detect the defect. The best color space that could produce excellent results close to the original defect was the RGB and the YCbCr showing more than 96% accuracy, due to the nature of the color arrangement. Therefore for any wood related machine vision grading or sorting system the suggested colour space could be used and will produce the best results.

2. The best NN structure was the Pattern net structure with less processing time and without over fitting problems like Cascade forward net and the optimal number of neurons were between 4 and 6 for mean input, and above 5 for c9 input. Hence it is clear for the effective detection the relation between the number of inputs and the number of neurons plays an important role and the suggested neuron numbers will be perfect to identify the defect.

3. The combination of the color space was seen to produce the excellent result of 99% accuracy on choosing the perfect neuron number. Therefore it is possible to use this in wood grading and defect detection system.

4. The proposal for the design with all the necessary parts was given. Therefore it is likely to develop the system with suggested parts. A prototype setup was made in Assoc Prof Vidas Raudonis Laboratory with the available parts.

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APPENDIX 1

```matlab
hiddenLayerSize = 2;
net = patternnet(hiddenLayerSize);

    % Train the Network
    [net,tr] = trainscg(net,tot_RGCBR,tar3_orgimg);
    %%

b = imread('C:\Users\madhu\Desktop\flash pic\New folder\N (1).JPG');
%  b = imresize(a1, [300 200])
  figure(1)
  imshow(b)
   x1=rgb2ycbcr(b)
  y1 = double(x1(:,:,1)); % Red channel
cb1 = double(x1(:,:,2)); % Green channel
rc1 = double(x1(:,:,3)); % Blue channel
[n m k] = size(b);




    r1 = double(b(:,:,1)); % Red channel
g1 = double(b(:,:,2)); % Green channel
b1 = double(b(:,:,3)); % Blue channel


    cr1=im2col(r1,[3 3]);
    mr1=mean(cr1,1);
    sdr1=std(cr1,1);
    skr1=skewness(cr1,1);

    cg1=im2col(g1,[3 3]);
    mg1=mean(cg1,1);
    sdg1=std(cg1,1);
    skg1=skewness(cg1,1);

%     cb1=im2col(nb1,[3 3]);
%     mb1=mean(cb1,1);
%     sdb1=std(cb1,1);
%     skb1=skewness(cb1,1);

rc2=im2col(y1,[3 3]);
    my2=mean(rc2,1);
cg2=im2col(cb1,[3 3]);
    mg2=mean(cg2,1);
cb2=im2col(rc1,[3 3]);
    mb2=mean(cb2,1);

%     c91=[cr1' cg1' cb1']';
    m1=[mr1' mg1' mg2' mb2'];
%     sd1=[sdr1' sdg1' sdb1'];
%     sk1=[skr1' skg1' skb1'];

out = net(m1');
```

```matlab
 bw3 = reshape(out(3,:),n-2,m-2);
 figure(5)
 imshow(bw3,[])
 bw2 = reshape(out(2,:),n-2,m-2);
figure(4)
 imshow(bw2,[])
 bw1 = reshape(out(1,:),n-2,m-2);
 figure(3)
 imshow(bw1,[])
   imwrite(bw1,'E:\mad_result\rgbycbr\neu2\n1_1.bmp', 'bmp');
   imwrite(bw2,'E:\mad_result\rgbycbr\neu2\n1_2.bmp', 'bmp');
```

APPENDIX 2

```matlab
a1 = imread('E:\mad_result\contrast pattern\ntsc\mean\neu4\n1_2.bmp')
a2 = imread('E:\mad_result\contrast pattern\ntsc\mean\neu4\n1_1.bmp')
figure(5)

subplot(2,4,1)
 imshow(a1)
 title('NN DEFECT OP','Fontsize',12)
tic;


BW = im2bw(a1,0.73);
t = toc;

disp(['time THRESHOLG IMAGE 1: ' num2str(t)])
subplot(2,4,2)

imshow(BW)
title('BW THRESHOLD OP','Fontsize',12)
SE = strel('arbitrary',eye(4));
 SE1 = strel('rectangle',[6 6]);

tic;
BW1 = imerode(BW,SE);
t = toc;
disp(['time Eroded image 1: ' num2str(t)])
subplot(2,4,3)



imshow(BW1)
title('ERODED IMAGE','Fontsize',12)
se = strel('disk',10);
% Perform a morphological close operation on the image.
tic;
 BW3 = imclose(BW1,SE1);
 subplot(2,4,4)
 t = toc;
disp(['time imclose image 1: ' num2str(t)])
 imshow(BW3)

 title('IMCLOSED IMAGE','Fontsize',12)
```

```matlab
 [n m]=size(BW3);

tic;
C=imfill(BW3,'holes');
 t = toc;
disp(['time imfill image 1: ' num2str(t)])
subplot(2,4,5)

 imshow(C)
title('FILLED IMAGE','Fontsize',12)


 %% REGION PROPERTIES
 %Label the image
[Label,Total]=bwlabel(C,8);
%Object Number
tic;
s  = regionprops(Label,
'centroid','area','Perimeter','MinorAxisLength','MajorAxisLength');  %%cc =
sort(area)
area = cat(1,s.Area);

cc = zeros(size(C));
[maxx maxxInd] = max(area);
cc(find(Label==maxxInd)) = 1;
sor=sort(area);
anWhite1 = nnz(C);
numberOfPixels = numel(C);
%sprintf('The number of white pixels %d',nWhite);


ar_more_250_1=0;
for i=1:1:Total

if area(i)>250

    ar_more_250_1=area(i)+ar_more_250_1;
end
end


 t = toc;
disp(['time area 1: ' num2str(t)])
%% WHOLE STICK


 %figure(6)
 subplot(2,4,6)
 imshow(a2)
 title('NN STICK OP','Fontsize',12)

BW_B = im2bw(a2,0.7);
%figure(7)
subplot(2,4,7)
imshow(BW_B)
 title('BW THRESHOLD IMAGE','Fontsize',12)
```

```matlab
SE = strel('arbitrary',eye(8));
% SE = strel('rectangle',[6 6]);
BW1_B = imerode(BW_B,SE);
% figure(8)
% imshow(BW1_B)
% BW2 = imdilate(BW1,SE)
% figure(4)
% imshow(BW2)
se = strel('disk',10);
 BW3_B = imclose(BW1_B,se);
%  figure(9)
%  imshow(BW3_B)
 [n m]=size(BW3_B);

BW4_B= imcomplement(BW3_B);
%figure(10)
 %imshow(BW4_B)
 C1=imfill(BW4_B,'holes');
%figure(10)

 subplot(2,4,8)
  imshow(C1)
    title('FINAL IMAGE','Fontsize',12)

nWhite_B = nnz(BW4_B);
numberOfPixels_B = numel(BW3_B);
[Label1,Total1]=bwlabel(C1,8);

%Object Number
s1  = regionprops(Label1,
'centroid','area','Perimeter','MinorAxisLength','MajorAxisLength');  %%cc =
sort(area)
area1 = cat(1,s1.Area);

cc1= zeros(size(C1));
[maxx1 maxxInd1] = max(area1);
cc(find(Label==maxxInd1)) = 1;
sor=sort(area1);
```