SPOT WELDING QUALITY CHECK USING ARTIFICIAL INTELLIGENCE

JAGADISA A/L RAJARATHNAM

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

SPOT WELDING QUALITY CHECK USING ARTIFICIAL INTELLIGENCE

JAGADISA A/L RAJARATHNAM

THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF INDUSTRIAL ELECTRONICS AND CONTROL ENGINEERING

FACULTY OF ENGINEERING UNIVERSITY OF MALAYA KUALA LUMPUR

2018

UNIVERSITY OF MALAYA ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: JAGADISA

Matric No: KQC160009

Name of Degree:

MASTER OF INDUSTRIAL ELECTRONICS AND CONTROL ENGINEERING

Title of Project Paper/Research Report/Dissertation/Thesis ("this Work"):

SPOT WELDING QUALITY CHECK USING ARTIFICIAL INTELLIGENCE

USING AI

Field of Study: ARTIFICIAL INTELLIGENCE

I do solemnly and sincerely declare that:

1. (1) I am the sole author/writer of this Work;
2. (2) This Work is original;
3. (3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;
4. (4) I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;
5. (5) I hereby assign all and every rights in the copyright to this Work to the University of Malaya ("UM"), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained;
6. (6) I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by UM.

Candidate's Signature Date:

Subscribed and solemnly declared before,

Witness's Signature Date:

Name:

Designation:

SPOT WELDING QUALITY CHECK USING ARTIFICIAL INTELLIGENCE

ABSTRACT

Spot welding is widely used in the automotive industry as the preferred method to weld the body parts. However, a bad quality spot weld can cause problems to the production line such as downtime and monetary losses. It can even cause fatal accidents if the defect body reaches the customer. The current methods of evaluating the quality of a spot weld is either too slow or it is not sufficiently accurate. These methods include, isolating a body to perform destructive test or by using ultrasonic test. This thesis studies on determining the spot weld quality based on a captured image of the spot point. In order to accurately determine the quality, a complex image processing algorithm is applied. The module is fed with pictures of spot welding with good quality and spot welding with bad quality. It then learns the attributes of these images and builds a database with corresponding figures for the two categories. These figures are then used to determine the quality of spot welds. To further enhance the system, artificial intelligence is introduced to it. The system uses the images to build its database and as the size of the database increases, it becomes more accurate. The model has an accuracy of 85% for positive image detection and 75% for negative image detection. It has a marking accuracy of 100% for detecting the spot welding regardless of positive or negative.

Keywords: spot welding, image processing. artificial intelligence, neural network, k-nearest neighbor

PENENTUAN KUALITI KIMPALAN SPOT DENGAN MENGUNNAKAN ARTIFICIAL INTELLIGENCE

ABSTRAK

Proses pengimpalan secara spot digunakan di dalam industry automotive secara luas dan sebagai cara pengimpalan yang utama. Tetapi, pengimpalan spot yang mempunyai kualiti yang tidak bagus boleh menyababkan masalah seperti line yang berhenti di dalam proses pembuatan kilang dan kerugian dari segi kewangan. Ia juga boleh menyababkan kemalangan maut jika masalah ini tidak diselesaikan dan sampai kepada pengunna. Cara penentuan sekarang tidak efisyen dan terlalu lambat. Ia melibatkan mengeluarkan body kereta daripada proses pembuatan untuk membuat pemeriksaan secara proses "destructive test" dan secara pemiriksaan mengunnakan alat ultrasonik. Di dalam kajiana ini, process baru yang mengunakan gambar kimpalan spot tersebut dan menentukan kualitinya. Untuk menentukan kualitinya dengan ketepatan yng tinggi, Teknik pemprosesan gambar yang tinggi akan digunakan. Contoh gambar kimpalan yang mempunyai kualiti yang baik dan tidak berkualiti akan digunakan. Sistem ini akan mempelajari secara automatic kriteria-kriteria di dalam gambar-gambar tersebut dan akan membentuk standard. Ia akan digunakan untuk menentukan kualiti kimpalan. Sistem ini mengunnakan gambar baru itu untuk memperbesarkan databasenya dan ketepatannya akan bertambah dengan lebih gambar. Model ini berjaya memperolehi ketepatan 85% untuk gambar positif dan 75% untuk gambar negatif. Ketepatan menentukan kawasaan kimpalan adalah 100%

Kata Kunci: Kimpalan spot, pemprosesan gambar, neural network, artificial intelligence, k-nearest neighbour

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my friends and family who helped me in completing this Research Project. Special thanks goes to my project supervisor, Ir. Dr. Chuah Joon Huang who has guided me throughout the process of completing this research project in the VLSI and Image Processing (VIP) Research Lab. He has contributed ideas, guidance, encouragement, and supervision in ensuring the progress of this project runs smoothly as scheduled. Special thanks also goes to the Faculty of Engineering which has provided us students with all the necessary material needed to complete this report. Last but not least, I would like to thanks my mother for her continuous support and encouragement throughout my postgraduate study in the University of Malaya (UM).

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
BLE	-	Bluetooth low energy
CNN	-	Convolution Neural Network
CPU	-	Central processing unit
GPU	-	Graphic processing unit
HDD	-	Hard disk drive
kNN	-	k-Nearest Neighbour
LCD	-	Liquid crystal display
NDT	-	Non-destructive Test
NVH	-	Noise, Vibration and Harshness
ROI	-	Return of investment
SOP	-	Standard Operating Procedure
SSD	-	Solid state drive
UM	-	University of Malaya
USB	-	Universal serial bus

LIST OF APPENDICES

CHAPTER 1 : INTRODUCTION

1.1 Research Background

Spot welding is a common type of welding used largely in the manufacturing industry. It is used to join metal parts together to form a product. Spot welding provides a cleaner look compared to other types of welding. Apart from that, spot welding maintains the flatness of the surface in which it is applied on. The automobile manufacturing industry uses spot welding to weld vehicle body. The welding guns are used to spot the parts right after the metals are stamped at the stamping plant. The parts are then combined to form different sections of the vehicle i.e. Front End, Rear Floor, Side Structure and Under Body. Other attachment parts such as the doors, hood, trunk lid and roof also use spot welding to combine segments. These processes can be done in both manual method, semi-automated or even fully-automated method. In fully automated method, the entire line utilizes robots that carries the welding guns. The robots are controlled by programs that run from the Programmable Logic Controller unit. The spot points are all pre-taught to the robot using a method known as "teaching". The teaching is done by the line installer using the teaching pendant. Every time the spot points needs to be adjusted or if there are any additional spot points to be added, the robot has to be thought again. In the manual mode, welding guns are controlled by the workers and they spot on points according to the standard operating procedures (SOP). The fully automated mode provides a much more accurate and consistent spot point.

The quality of the weld depends on various factors and while some can be controlled, such as the current and force, there are other factors that can cause unpredicted behaviours to the welding process:

a) Welding robot problems, e.g. Servo motor failure, servo amplifier failure

b) Welding gun tip wear

c) Misalignment of welding gun holder

d) Welding cable failure

e) Out of spec welding cable or tip

f) Inconsistent weld force

The problems mentioned above can cause over or under force which can affect the weld quality and the severity of a bad spot point can be anywhere between a minor vibration noise or part detachment.

1.2 Problem Statement

Unlike the usual arc or mig welding, spot welding is more suited for high speed process. Welding guns can transfer high current in split seconds, welding two or more parts together instantly. There are usually more than one welding robot in a stage that spots different parts of the body. While it is easy to detect the quality of arc welding by its burn pattern, it is usually harder to recognize a bad spot weld because the process is fast enough to go unnoticed and there is no particular pattern to it. However, there are several ways to detect a bad spot weld.

Ultrasonic weld detectors can check the quality of a spot weld by using sound waves. This method of spot weld testing requires coupling sound into a cup-shaped weld in a small diameter (3mm to 6mm) and generating multiple back wall echoes at high frequency. In a good weld, the spacing between echoes will be proportional to the thickness of the weld. Different part thickness has different sound wave properties. Most ultrasonic devices can be programmed to detect weld qualities of different types of parts with different thickness. The echo patterns can be used to determine the quality of the weld and even if there are any problems with the welding equipment. This process takes a longer time as the ultrasonic weld detector cannot check more than 1 spot point at a time. Besides, a process like this cannot be implemented as an online checking method. The moving body has to be stopped and isolated for inspections to be performed.

A more conventional method is by using destructive test. A part is deliberately separated by using force to determine the weld strength. In the automotive industry, workers usually separate the parts using a chisel or even by hand. This test is fast, accurate and does not require any device to be performed. However, this test requires the parts to be tempered and if the parts separate, they will have to be put on the jig again to be re-weld. They also involve manpower, and this increases the cost per unit car. Manpower allocated specially to a minor task as such is considered to be a waste in the automobile industry.

In both of the methods, a production line has to be stopped to perform the test. There are usually hundreds of welding robots and manual welding guns in a line and the quality of the welding can only be checked after the body has reached the final stages. They are usually done in a random check method. One body is pulled out every hour and all the weld quality are checked for about 10 to 15 minutes. If a problem is spotted, all the body in the past 1 hour has to be checked for any problems. This can cause a huge downtime and losses as the complete bodies may have entered a different stage or even to the next shop which is the painting shop. Apart from that, there are some points that are simply impossible to be fixed after the body has passed a certain painting process. Hence, the body will have to be scrapped and this is a huge monetary loss. Another worrying factor is the use of human to detect a crucial safety point. Workers may unintentionally or even intentionally skip the checking process, and this can cause parts with bad weld to pass the line without any rectification. In this case, the body can even reach a customer and cause a fatal accident when the join eventually gives way.

1.3 Aim of Investigation

The aim of this research is to design a system that can check the quality without any of the problems stated in Sub-chapter 1.2 Problem Statement. A spot welding quality check process will be implemented using artificial intelligence. The system will use cameras that are mounted on a jig and uses a process to monitor every spot weld pattern and determine if there is no fusion in the weld. The objectives of the project are:

a) Efficiently detect the weld quality of a spot weld without the need of human workers
b) Perform the test without the need to isolate the body from the production line
c) Perform the test without the need to stop the production line at various stages
d) Avoid bad spot welds to go undetected

1.4 Scope of Work

The scope of this project is to carry out study on the patterns produced by a spot welding gun on a typical 2-layer, uncoated car body metal. A database of photos for positive (good quality spot welding) and negative (bad quality spot welding) attributes is obtained by taking photos of spot welding on actual test pieces. A program with self-learning capabilities will then be used to build a comparison technique to differentiate between positive and negative spot welds. It will capture images and compare with the database online. As more and more photos are added to the database, it is able to detect and differentiate more efficiently. A hardware module is planned, designed and constructed to implement the learning system. The system is then evaluated by calculating its accuracy in determining positive and negative images correctly. The system can be used in various industries that involve spot welding process.

CHAPTER 2 : LITERATURE REVIEW

The literature review highlights the basic ideas of all the elements involved in this project. All the elements are used in implementing the Artificial Intelligence to determine the quality of a spot point. The crucial parts are towards the end in which a suitable system is modelled for the project and a suitable neural network algorithm is implemented for the AI learning process.

2.1 Introduction

Spot welds are used to join metal sheets together. In the automotive industry, these spot sheets can have thickness between 0.3mm and 5mm (N. Wylie, 2009). Using the electrode gun tips, current is passed through the metal sheets from the top and bottom. The heat that melts the two parts together is generated by the resistance in the flow of current between the sheets. The resistance varies between different surface conditions, material and the electrode caps that are used. The formula below shows the relation between heat, resistance and current (N. Wylie, 2009).

$$H = I^2RT$$

The force provided by the electrodes contains the molten metal in between the sheets. The fusion area is known as a weld nugget as illustrated in Figure 2-1.

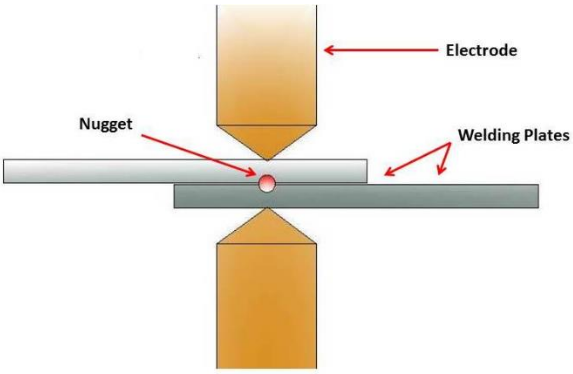


Figure 2-1 Spot Weld

A minimum acceptable size for the nugget ensures that the weld is strong enough to hold the pieces. When the current is increased beyond the capability of the electrodes to contain the molten metal, a splash may occur. When a splash occurs, the electrodes go deeper into the metal causing discontinuities in the weld. This is also a reason for poor weld quality and it can severely damage the weld nugget making it detectable by looking at it.

2.2 Spot Welding Quality Check

The automobile industry is rapidly growing, and technology and the welding quality is the base of every vehicle's safety requirement. Spot welding determines the strength of the car and also the quality and NVH in term of vibration. Bad spot welding is a huge problem in the industry and when they are detected, the entire line has to be stopped and tests has to be done at various stages. If the body has passed the welding shop and has entered the painting shop or even until customers, it can cause a lot of monetary losses.

Welding robots can detect an over or under current in the welding process, but it can not usually check the actual welding pressure that is applied during the welding process. In most automotive companies, the destructive test remains as the most practical method of checking the quality of a spot weld. Apart from that, actual robot and manual gun pressure is also checked at random times using a welding gun pressure gauge. To decrease the possibility of bad spot welding going out, more checks has to be conducted. However, this requires more manpower and it also means that the cycle time is increased because time is allocated for random checks.

Figure 2-3 : Spot Welding Gun

Figure 2-2 Welding Gun Pressure Gauge

2.3 Non-destructive Test (NDT)

Non-destructive test (NDT) provides the efficiency that is much needed. Ultrasonic pulse-echo NDT is well known in the industry and is a well-established method for checking the integrity of spot welds without the need of destructive test as it can identify whether or not a weld contains cracks or voids. There are several studies that are being done in this field to come out with newer methods to check on spot weld quality. One of these uses the results from the online measured indentation from servo encoder (Lai Xinmin, 2017). However, this process possesses several problems and can only be implemented in robotic guns. The implementation also defers between make of the robots. Some robots do not use a typical encoder to records its position.

Spot welding quality can also often be detected by looking at the welding nugget. A bad spot can be quite obvious but detecting it in a production line is next to impossible. Besides, one worker can only check on a few spots and it will require many quality inspectors to check all spot welding on a car.

2.4 Module Building

An automated weld check will be a good replacement to the manpower and it will also increase the efficiency. It should accurately detect the weld quality based on its pattern. It should also provide some kind of warning to not allow any bad spot welds to pass the production line. Depending on the image, the data will then be stored automatically to increase the database of the machine. The flow diagram below describes the proposed module that will be used for the detection system. In a real-life situation, the camera is turned on and the system monitors the wedding spot location. A box is drawn around the spot weld to indicate that a pattern is present.

The pattern is then compared to the attributes in the database. If it matches the positive image, the box turns green and if it matches the negative images, the box turns red. At the same time, the image is stored in the corresponding database and is used as an additional learning material.

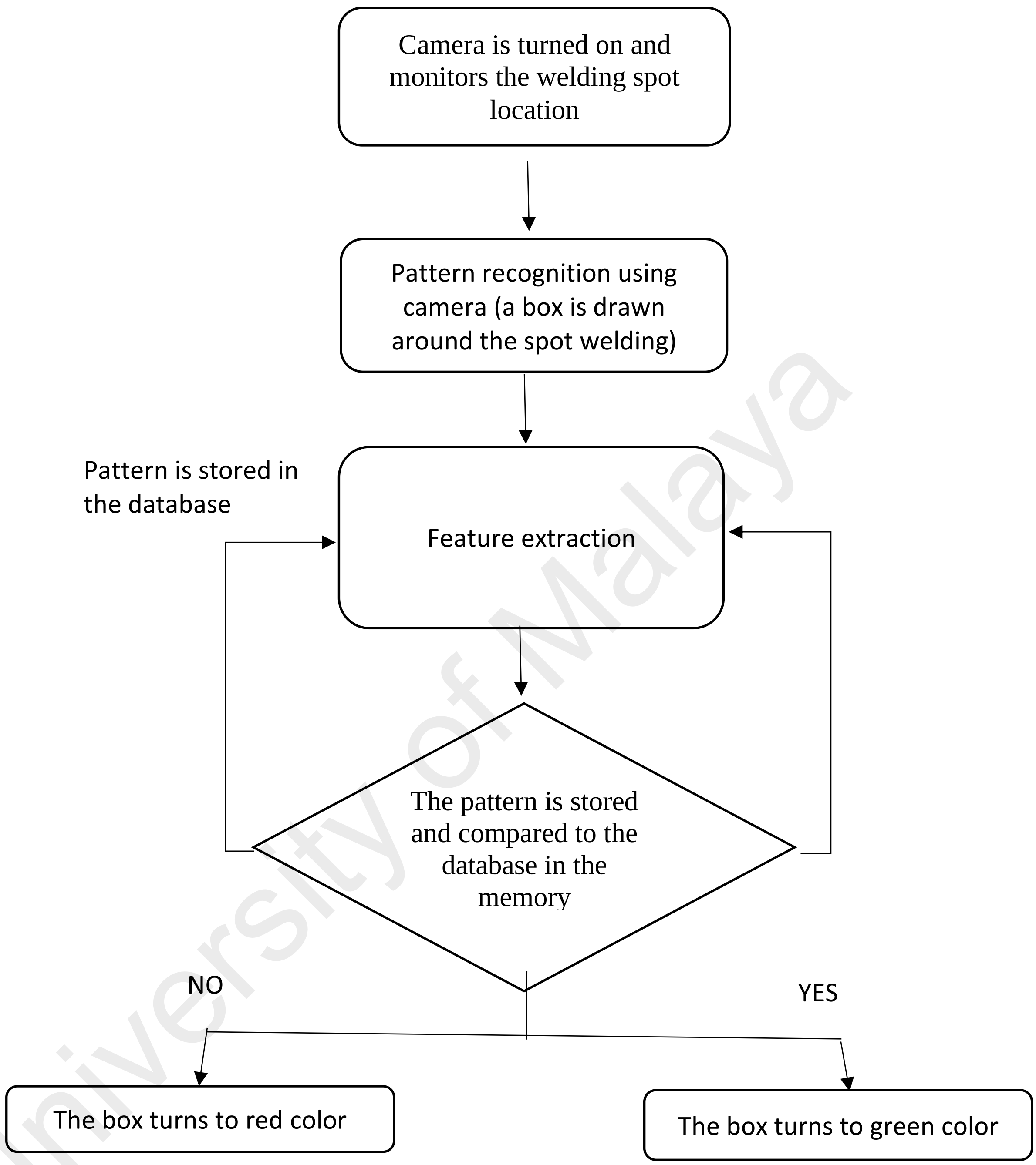


Figure 2-4 Module building

2.4.1 Image Processing

Image processing is the process of analysing and manipulating the images that are to be stored in the database. Attributes of the images are collected to be used as a benchmark for determining the traits in the spot point quality. Digital image processing generally goes through three phases (Anbarjafari, 2014). These includes:

a) Pre-processing

b) Enhancement

c) Display

d) Information extraction

A digital image consists of individual pixels, each with its own value corresponding to its colour and intensity value. In pre-processing, the image is evaluated based on the amount of information it gives and the amount of information that is needed. The image is manipulated in the enhancement phase to obtain the required information from it. This includes enhancing the colours, brightness, contrast and shadows.

The picture can also be manipulated to reduce the amount of information it carries. For example, if the processing needs to be done at high speed, the image size can be reduced. The number of pixels is reduced and hence, the amount of information it carries is also reduced. Apart from that, the picture can also be converted into grayscale to reduce the amount of information each pixel carries. Reducing the number of pixels and the information in each pixel is crucial to reduce the amount of data that requires processing. The image is then displayed as a new image with only the required information. The data that this image can give is directly related to the required data and the processing capabilities. If the data displayed is too big, a higher processing power is needed and can potentially increase the required resources. An efficient system will only display the crucial attributes in the image. For example, if the goal is to study on the ripeness of a red Apple based on the intensity of its colour, the image can be converted to grayscale. Its level of ripeness can be evaluated from the intensity of the grey colour. However, in some cases, the image has to be unscaled. This is usually true for high accuracy face detection. The information extraction phase includes extracting a few attributes of the image. This can be colours, measurements of certain elements, ratio of the elements, opacity, intensity or even brightness. These attributes are used to classify the images based on their characteristics. Higher processing power is needed when the number of attributes is bigger. There are 3 types of image processing capabilities:

Table 1 Image Processing Types

Low Level Process	Mid-Level Process	High Level process
Input: Image	Input: Image	Input: Attributes
Output: Image	Output: Attributes	Output: Understanding
Example: Noise removal, image sharpening	Example: Object recognition, segmentation	Example: Scene understanding, autonomous navigation

2.4.2 Artificial Intelligence

Artificial Intelligence (AI) is the intelligence demonstrated by any type of machine (Wikipedia, 2018). Artificial intelligence mimics the intelligence displayed by humans and animals. Any machine or program that can perceive its surrounding and perform calculations based on this can be perceived as an AI instrument. Generally, AI is used as a method to substitute humans in certain tasks.

Artificial Intelligence has been used widely in recent times. Its biggest usage is in the gadget field. This includes mobile phones, tablets and computers. A simple example would be "Siri" or "Bixby", AI voice assistance by Apple and Google. Tesla, the electric car manufacturer has been pioneering the AI field in the self-driving cars in the past two years. Using sensors and cameras, a self-driving car can detect road signs, road markings, other cars and even humans inside and outside the car. Image processing is a big part in this as it enables the car's camera to detect and interpret signs and markings. AI is also used extensively in Google's search engine. With AI image processing, Google's image search can categorize images based on colour, size, type and people.

More complex usage of AI is used in super computers. They can perform complex calculation from very little input data or no data at all. This is known as unsupervised learning. Supervised learning uses example pairs (x, y) in which $x \in X, y \in Y$ and the aim is to find a function of $f: X \longrightarrow Y$ in the allowed classifications from the example (Varun KumarOjha, 2017) .

The traditional methods used in vision and machine learning for image processing cannot match human's performance on tasks like pattern recognition, hand writing recognition, hand written numbers or even symbols and sign. However, with deep learning, a computer can begin to recognize a more complex image. This can be done with the use of neural networks. Neural networks are connection systems inspired by the human brain network and are often used in developing AI modules.

An article by Dan Ciresan, Ueli Meier and Jurgen Schmidhuber studies on a Multi-Column Deep Neural Network for image classification (Dan Ciresan, 2012). DNN has a hundred of maps per layer as opposed to the standard method which only has a few maps per layer. As a result of this and faster processors and graphic processing units (GPU), a result which is said to be human like replication is produced. The method is tested on various kinds of data including road signs, writing in English and even in isolated Chinese characters.

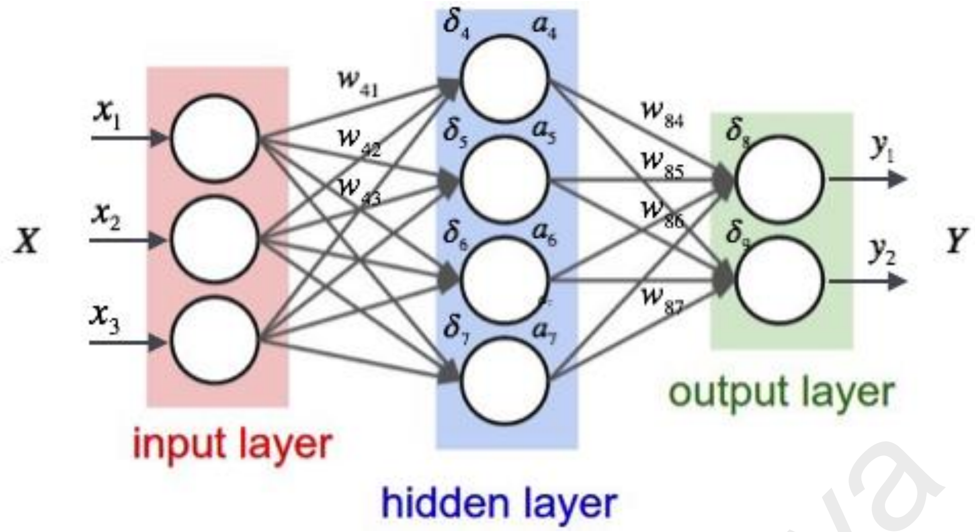


Figure 2-5 Neural Network *(Valkov, 2017)*

Figure 2-4 shows the basic network diagram of a neural network. The main idea is to implement the core algorithm that is used to train deep neural networks - backpropagation. Backpropagation is the backbone of neural networks. The algorithm has 3 subtasks:

- Make a forward pass
- Calculate the error
- Make backward pass (backpropagation)

For the first step, backpropagation uses the data and the weights of the network to compute a prediction. Next, the error is calculated based on early prediction and the given labels. The final step is to propagate the error through the network, starting from the final layer. Hence, the weights get updated incrementally based on the error. The error decreases as the learning process moves forward. With every decrease in error, the learning become more developed. The rate at which the error decreases relies hugely on the type of data that is fed to the system. Complex data for a rather simple detection system can take more time than a complex detection system.

Similar concepts are used in this project. The learning is a supervised, and all the data is given to the system for it to build characteristics to compare and categorize them. Data is given to the system in the simplest way possible.

2.4.3 Data Mining

Data mining is the process of extracting and generating information by studying on a suitable pattern for a large set of data.

Figure 2-6 Data mining from images

When one has a glance at the photos on top and a human, the person would be able to differentiate between the dog, man and cat. However, a machine does not work this way.

What the machine sees is a set of binary data representing different information in the images. The obvious method would be to apply some filters and perform feature extraction on the images. By applying the region of interest (ROI) classification for some images, the details of the x-coordinates and y-coordinates can be distinguished (Santosh Kumar Dash, 2016). Other advanced methods can also be used, such as applying filters to distance the differences in the photos.

2.4.4 kNN Classification

K nearest neighbours (kNN) is an algorithm that stores all data that is given to it and builds classification for new cases based on a similarity to the database (e.g., ratio, distance, colour functions) (Sayad, 2018). Each new data is classified by its nearest neighbour's vote. It is measured by a distance function.

There are three types of distance function:

a) Euclidean : $\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$

b) Manhattan : $\sum_{i=1}^{k}|x_i - y_i|$

c) Minkowski : $(\sum_{i=1}^{k}(|x_i - y_i|)^q)^{1/q}$

The three distance measuring functions above only work for continuous variables. For categorical variables, the Hamming distance must be used.

d) Hamming: $\sum_{i=1}^{k}|x_i - y_i|$

$x = y \Longrightarrow D = 0$

$x \neq y \Longrightarrow D = 1$

Choosing the best value for K is best done by inspecting the data first.

There are several improvements to the classic kNN algorithm. The first is known as Adaptive k-Nearest Neighbour. This concept is based on the principle that nearest neighbours will have similar attributes and thus it can be assumed that the data that is tested is the closest with its nearest neighbour in the data set. It is still most likely to adopt the same kNN algorithm at its nearest neighbour to get a correct classification. The advantage in this method is the k is now the fewest nearest neighbours a test data has to identify to get the correct classification. Hence, the optimal k gives the correct classification (Shiliang Sun, 2010).

Another enhanced version is by using K-Nearest Neighbour algorithm using information gain and clustering. In this method, pre-processing data provide the weight to different attributes. It determines the k value and divides the training data into different clusters. This creates a model for future classification process. This part happens once and after that, only the test data runs every time (Shweta Taneja, 2014). The pre-processing flow and classification process is shown in Figure 2-7.

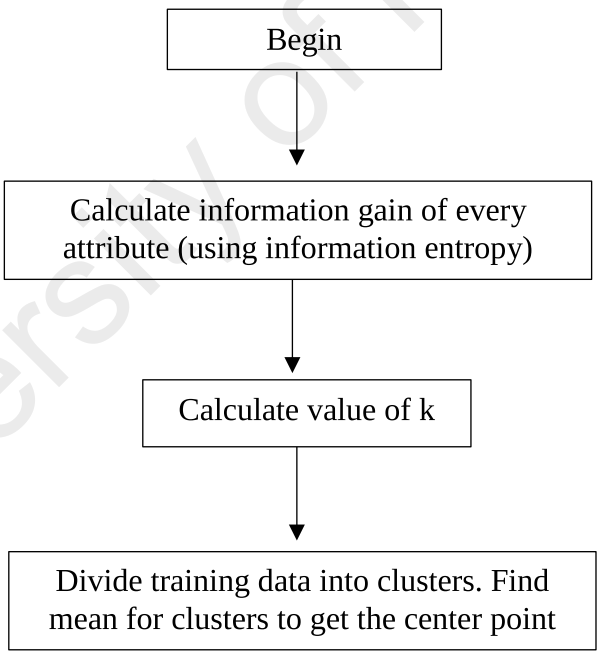


Figure 2-7 Data Pre-processing

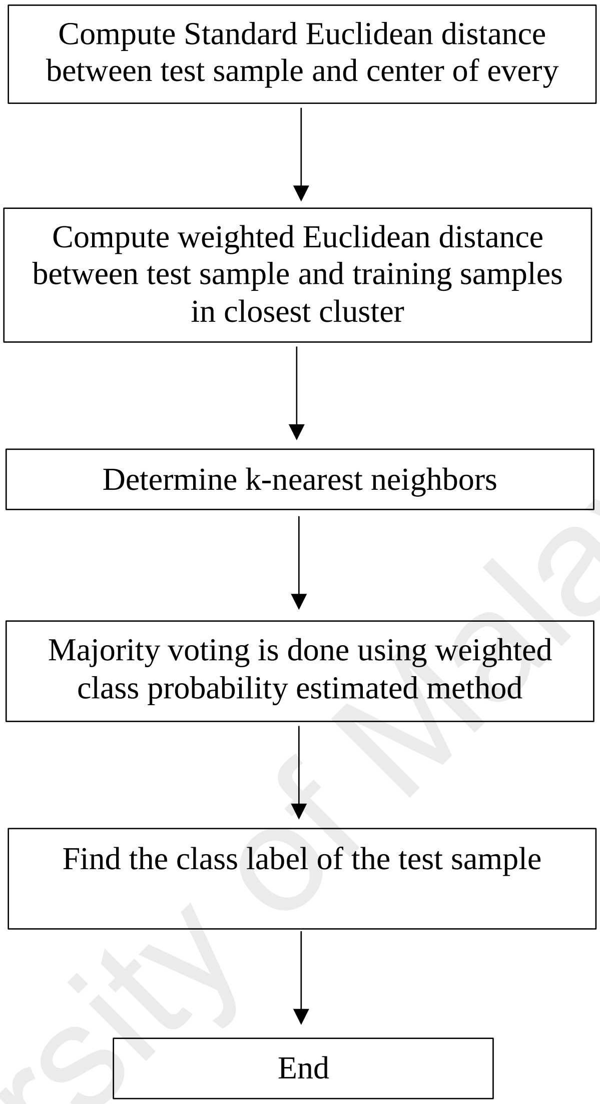


Figure 2-8 Image Classification

CHAPTER 3 : METHODOLOGY

3.1 Gant Chart

The project was started on February 2018 and the progress chart is as shown in the Gantt Chart below.

Activity	Feb		Mar				Apr				May			
	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
Research Project														
Literature Review														
Database collection														
Concept Development														
Testing														
Optimization														
Validation														
Research Report														
Submission														
Presentation														

3.2 Working Principle

The spot welding quality check is done by detecting the pattern of the spot weld. For the learning phase, a hardware is constructed to capture images of the spot points. This ensures that the learning phase is accurately done, and the system does not get a variety of images. Attributes of the images that determine the learned image includes:

a. Lighting
b. Aperture
c. ISO value
d. Brightness
e. Focus
f. Image size (pixels)

A change in the characteristics above would make the system pick up a wrong attribute to learn from. It would categorize the image in a wrong way. The details of this process in discussed in the next chapter.

3.2.1 Hardware

A hardware was constructed to take the photos of the spot points. The hardware acts as the central device between the spot points made by the welding machine and the program that determines the quality of the spot point. The list of components includes but are not limited to:

a) Raspberry Pi 3 – model B

Figure 3-1 Raspberry PI 3 (Front)

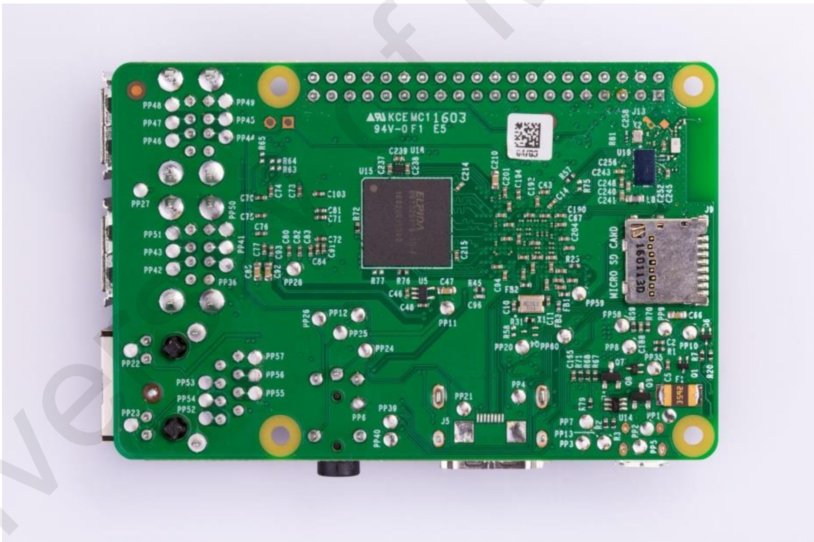


Figure 3-2 Raspberry Pi 3 (Back)

The Raspberry Pi 3 Model B is the third-generation Raspberry Pi. It replaced the Raspberry Pi 2 Model B in February 2016. Its specifications include (FOUNDATION, 2009):

- Quad Core 1.2GHz Broadcom BCM2837 64bit CPU
- 1GB RAM
- BCM43438 wireless LAN and Bluetooth Low Energy (BLE) on board

- 40-pin extended GPIO
- 4 USB 2 ports
- 4 Pole stereo output and composite video port
- Full size HDMI
- CSI camera port for connecting a Raspberry Pi camera
- DSI display port for connecting a Raspberry Pi display
- Micro SD port for loading operating system and storing data
- Upgraded switched Micro USB power source up to 2.5A

The Raspberry Pi kit is one of the most used programming kits in the world. Its simplicity, size and available support is a few of the reasons it is choose for mini projects such as this project. Its quad core processor and 1 GB RAM also allows it to handle complex algorithms quite well.

b) Raspberry PI camera kit

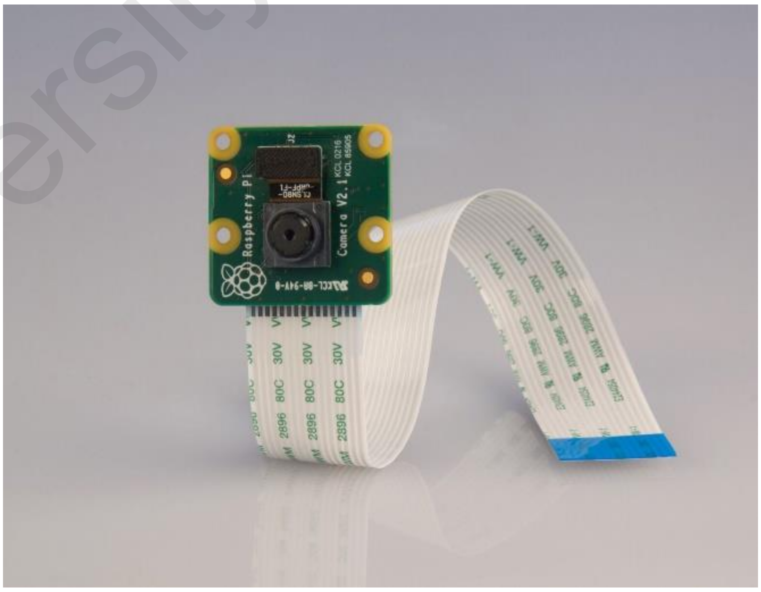


Figure 3-3 Raspberry Pi Camera Kit

The Raspberry Pi camera board plugs into camera board plugs directly into the CSI connector on the Raspberry Pi. It is able to snap photos at up to 5MP

(2593 x 1944 pixels) resolution, or 1080p HD video recording at 30fps. The camera features an Omnivision 5647 sensor with fixed focus. The module attaches to Raspberry Pi, by way of a 15 pin Ribbon Cable, to the dedicated 15 pin MIPI Camera Serial Interface (CSI).

c) 32GB microSD memory card

The 32GB microSD memory card is used to store the program to snap the photos and the photos of the spot welds.

d) Special jig

The jig is designed to hold the camera at a fixed height. It ensures that all the photos taken for the learning has the same size, focal length and definition. It is designed in white to allow enough light to enter and reflect on the test piece. This gives a uniform lighting for all images and they can be used accurately for the learning process.

e) Pi tft LCD 2.8” SPI

Figure 3-4 Pi TFT LCD

The Pi TFT LCD is a display designed specifically for the Raspberry Pi. In this project, it is used to read the running code on the Raspberry kit and to take the photos of the spot point. The TFT LCD display is at a maximum resolution of 320 x 480 pixels.

f) Raspberry Pi micro USB 2.5A power supply

The 2.5A power supply card provides the required power supply for the kit via a micro USB cable. This power supply, powers up the Raspberry Pi board and the display which is attached to it.

3.2.2 Others

a) Push buttons

Figure 3-5 Push Button

Push buttons are used to capture images of the spot weld. There are two push buttons connected to the circuit. The yellow push button takes a photo and saves it to the 'positive' result folder and the blue push button takes a photo and saves it to the 'negative' result folder. The push button is connected to an external board to avoid any excessive movement to the camera when the button is pressed, and the image is captured.

b) Computer

A windows-based computer is used to program, compile, debug and execute the program. The computer used in this project has the following specifications:

- Intel Core i7-7700 Processor (up to 4GHz)

- 16 GB DDR4- 2400 RAM
- NVIDIA Geforce GTX 1070 8GB GDDR 5
- 250 GB Solid State Drive
- 2 TB Hard Disk Drive
- USB 3.0 Port

Running a learned program can be quite small but training a program tends to use more resources. With a system like this, it takes around 4 hours for training with one set of raw data. However, those hardware requirements go up quickly as more data is thrown into the computer and asked to generate a result.

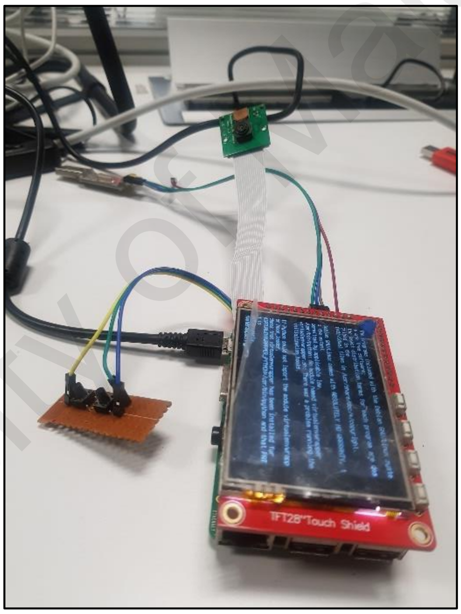


Figure 3-6 Complete Raspberry Pi kit with display and push buttons

3.2.3 Software

The programming part of the project was all done using Python 3. This programming language was conceived in the late 1980s and was implemented by Guido van Rossum in December 1989 in the Netherlands. Python 2.0 was later released in the year 2000 with better features in terms of memory management and support for Unicode (Venners, 2003). The major changes however, were in terms of support. Python was now a community backed ecosystem.

The version used in this project, Python 3.0, was released in 2008 after extensive testing. It is backward-incompatible and has many new features over the older versions, Python 2.6 and 2.7. The version 3 reduces the feature duplication. One major difference that makes Python 3 suitable for this project is its improvement and simplification in mathematical functions. For an example, 5 / 2 is 2 in the older python 2. In python 3, 5 / 2 is 2.5 and 5 // 2 is 2. Minor rectification like this has simplified the coding methods and reduced the time taken to code advance mathematical functions into python. Python is also appealing to everyone as it is a powerful, free and open source alternative to other programming methods.

As a result, a huge database of libraries is available on the internet. While other programming languages such as C programming lack mathematical functions, Python has an extensive support for it. Complex image processing can also be done by using MATLAB but there are several reasons why Python is chosen over MATLAB:

a) Coding in Python is more compact and readable
b) Python is mostly free and open source
c) Data structures in Python are better
d) Maintaining multiple version of shared libraries is easier with Python

Apart from this, the most important reason for choosing Python over MATLAB is because of its learning time. Implementing complex deep learning on MATLAB takes up a lot of resources and executing real-time image processing is next to impossible without a high-end computing device.

The Raspberry Pi kit gets its command from the computer. Hence, a SSH client was installed on the computer to access it via the USB cable. The SSH client used in this project is PuTTY. PuTTY is a SSH and telnet client for windows, created by Simon

Tatham. Like Python, it is an open source software that is supported by volunteers. PuTTY requires some simple setting; the baud rate at which the board can communicate at and the port number of the USB connection.

3.3 Material Selection

In modern cars, the biggest part of the mass comes from the body weight which is the steel used to form the car. Research has shown that the normal weight of a car has increased from 1,090 kg in 2007 to around 1,360 kg in 2017. The normal weight of SUVs has also increased from 1,360 kg to around 1,810 kg. This is quite obvious and noticeable as car sizes have been increasing over the years. A ‘B’ segment car today has the same volume as a ‘C’ segment car in 2007.

Steel is also used to create the underlying chassis, also known as the cage beneath the body. This part forms the frame of the vehicle which is the biggest safety concern in the automotive world. It protects the passengers and driver in the event of a crash. Door beams, side structure panels, roofs, hood and even the exhaust is made of steel. While back in the days most car manufacturers tend to use the same kind of steel, today’s manufacturers use various types of steel for the different parts of the car. The type of steel used between two manufacturers also differs by a lot. The steel is chosen based on their properties so parts of a vehicle that are rigid and absorb impact, known as the crumple zone, can be formed.

In this project, a single type of steel will be used to perform the spot welding. This metal will serve as a benchmark to the different kinds of steel. A test piece of the steel used in the side structure panel will be used to collect the data.

Figure 3-7 Welding test piece

It has a thickness of 0.5mm and is an uncoated sheet. The reason for this choice is because the 0.5mm uncoated sheet gives a very clear spot weld pattern and the difference between the weld with fusion and the weld without fusion is obvious. Thicker, coated panels will require much more data, processing power and learning space, hence increasing the cost of the project. A total of 32 test pieces were used in this project.

3.4 Programming

Building an Image processing model is a complex process. The flow chart in Figure 3-8 shows the steps involved in the programming process.

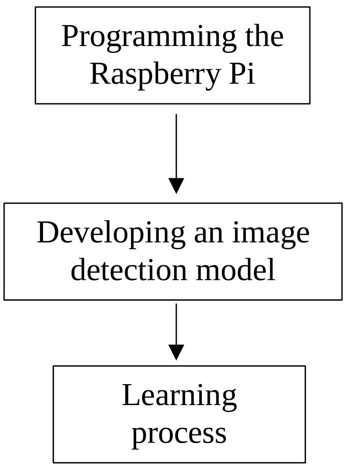


Figure 3-8 Programming Process

3.4.1 Raspberry Pi

The Raspberry Pi unit runs Python flawlessly making a seamless integration between software and hardware. The first step in the data collection stage was to take photos of the welded test pieces. To standardize the photos taken, the Raspberry Pi's camera kit was used. The images taken by the camera were automatically saved with a resolution of 320 x 240 pixels.

Several instructions set for controlling the raspberry pi are to be taken note of:

a) "Python cam2.py.3" activates the camera for taking photos
b) Pressing on the yellow push button snaps an image and saves it in the "positive" folder. The blue button saves the image in the "negative" folder
c) "tar -czvf positive.tar.gz positive" and "tar -czvf negative.tar.gz negative" compresses the photos in the positive and negative folder into and saves it in a zip file.
d) "Curl –upload-file ./positive.tar.gz https://transfer.sh/positive.tar.gz && rm -rf positive.tar.gz" and "Curl –upload-file ./negaive.tar.gz https://transfer.sh/negative.tar.gz && rm -rf negative.tar.gz" uploads the compressed zip folders to transfer.sh website which is an easy file sharing website hosted for Raspberry Pi users. After the transfer is completed, the zip file is deleted from the memory.
e) "rm -rf" deletes all the photos in the current folder
f) "mkdir positive" and "mkdir negative" creates the positive and negative folders
g) "shutdown -h now" to shut down the Raspberry Pi
h) "ls positive" and "ls negative" to check the contents of a folder

3.4.2 Data collection

The image detection model is the most crucial part of the project. It is the base for the learning process.

The following steps are done for the collections of the photos:

1. Spot welding the test pieces. Each test piece can have between 20 to 28 spots

Figure 3-9 Spot welding on the test piece

Figure 3-10 Test piece with spot welding

2. Taking photos of the spot points

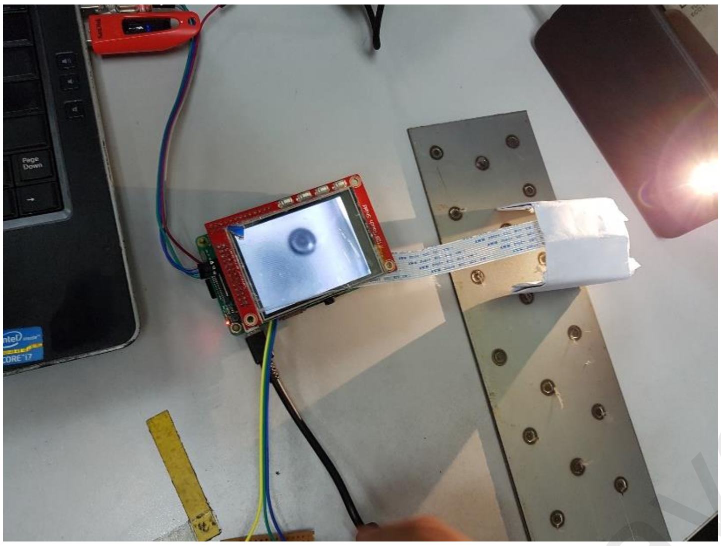


Figure 3-11 Taking photos of the spot points

3. Compressing the photos into a zip folder on the Raspberry Pi kit
4. Uploading the files to “transfer.sh” website

3.4.3 Pre-modelling

Before the modelling was done, the photos obtained had to be perfect for the learning process. Trials and corrections had to be made to obtain images that are uniform in lighting and colour. Several problems were found when the photos were first taken. These problems are to be rectified before the learning models were created and characteristics were analysed.

The best material to get a clear difference between the weld with fusion and weld with no fusion was found to be the uncoated test piece with thickness of 0.5mm. The current was set at 8.5 kA. This value can increase up to 13 kA for coated parts with higher thickness. One major problem was found with the red indicator light next to the camera. When photos of the test piece were taken there was a red reflection on the photo. This gave the photos false criteria. The intensity of the red colour would have been picked as criteria if the learning process was started.

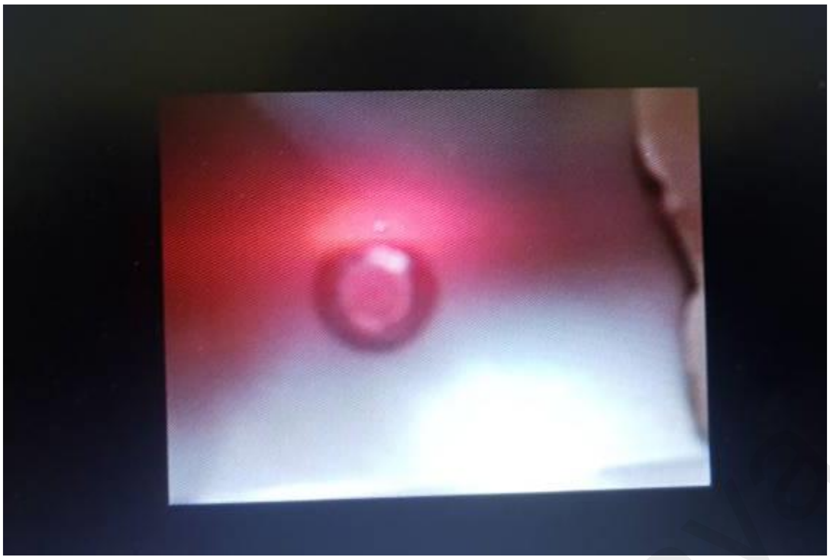


Figure 3-12 Image With the Red LED ON

The LED indicator was covered with a tape and photos were than taken without the reflection.

Another problem faced during the data collection process was with the inconsistent lighting. This was fixed by focusing a smartphone's flashlight on the opening of the jig. The light measure inside the jig, under the camera was about 320 lux. Coupled with the white surface of the paper jig, this light was enough to give an even white lighting to the entire spot point in the frame.

Unlike the human eyes, image processing using machine only needs a small amount of detail. These details are then used to build characteristics for the neural network and further algorithms can be used to enhance the learning. To simplify the both the learning process and the data collection process, the photos should be taken with only the most necessary details. In other words, the size of each data has to be as small as possible. Initially the compression was implemented in the photo saving stage. Only necessary information of the photo was saved. In this case, a gradient image was saved with only the difference from the backplane. However, the images that was obtained lack too much of information as the spot point simply wasn't defined enough for this kind of compression.

Figure 3-13 Image With Gradient Filter

The images were then taken without compressions. However, they were taken with a reduced size, 320 x 240 pixels. There were few reasons for this:

a) To reduce the image capturing time because the camera had a slow shutter speed
b) To reduce the size of data stored on the memory card
c) The dataset was wirelessly uploaded to transfer.com, a cloud base storage system. A large file would take a lot of time to upload.
d) The processing time would take much longer with a bigger image. This is because the computer has to process more details and learn more.

Sample good quality spot points were saved to the positive folder and spot points with bad quality (no fusion) we saved in the negative folder.

Figure 3-14 Positive Images

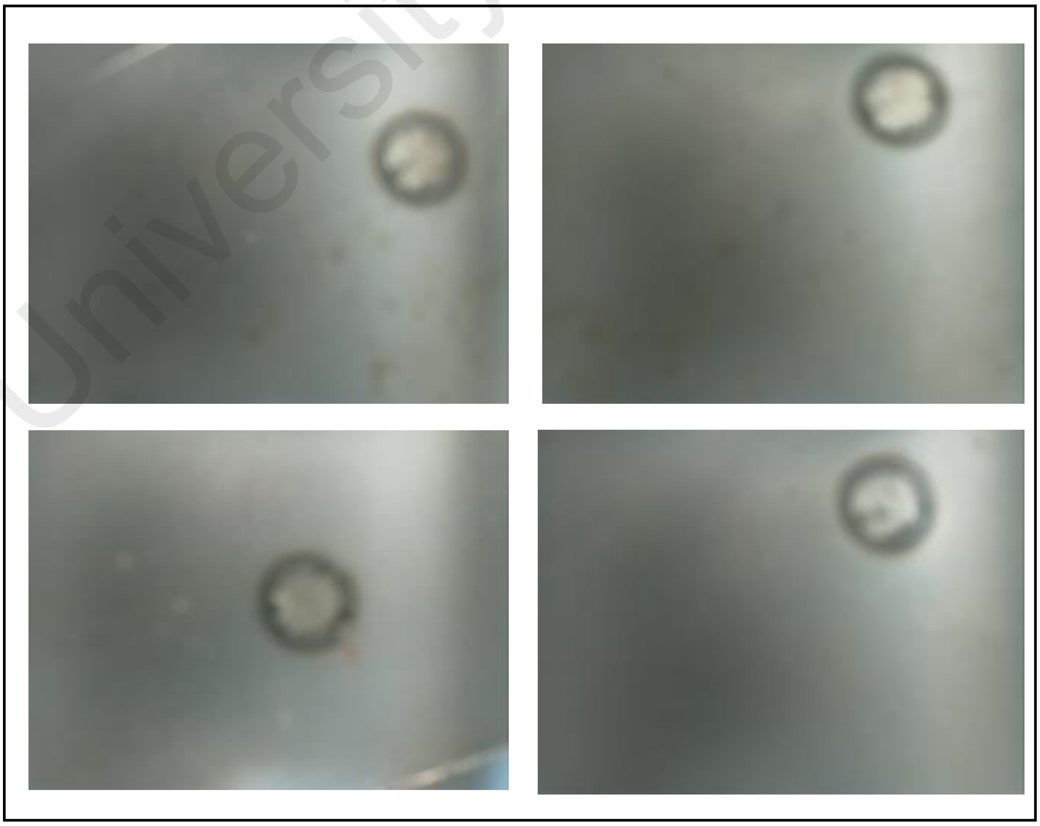


Figure 3-15 Negative Images

A total of 489 positive images were obtained. All were spot with the same welding parameters:

Current setting: 8.5 kA

Force setting: 2.0 kN

Welding Gun type: C-Gun

Brand: Dengensha

The negative images were obtained by lowering the transformer ratio on the timer unit.

Figure 3-16 Welding gun timer unit

This reduces the current for the welding process which effects the quality of the welding. However, there are other ways to cause a spot point to not have fusion. This will be discussed further in Chapter 5. A total of 385 of bad spot welding images were used as the negative image set and an additional 252 images of various unrelated photos were used to add to the learning of negative image.

The images were then changed from RGB to grayscale to have a single scale matric for the image in the x- and y- axis. This further reduces their size and remove details that are not needed such as colours and lighting. Using the RGB models will mean that the cascades will have to be built for all the R, G and B modes. The boxes will also have to be drawn for all three modes. Apart from that, the accuracy will also drop if the model is built in RGB. This is because the colours vary by some degree. When converted to grayscale, only the brightness is noticed as it is the only constant element. The size of the image is finally reduced to only 34 kb. The model could be run easily with this size. It can also be noticed that the image has reduced to very flat image with no information of anything below or above 90° of the spot point. These leave the image with only data from x-axis and y-axis.

Figure 3-17 Grayscale image

3.4.4 Modelling

Classification is a supervised procedure that learns to classify new data which is in this case, images, based on learning from a training set of instances that have been properly labelled by machine or human with the correct classes. The training data are vectors, each with a class label. The classification problem can be stated as follows: given training data produce a rule (or "classifier") h, such that h(x) can be evaluated for any possible value of x (not just those included in the training data). Several methods were tested for modelling before a final output was produced. The libraries supported by Python were used to perform the modelling. The first method applied is known as Tensor flow. Tensor flow is an open source machine learning framework for all kinds of works. It is able to perform numerical computations at a higher level. In addition, because the learning and processing can be left to any platform, a machines full performance can be used to do the computation (McClure, 2017). This keeps most of the image processing work to the graphics card and the modelling to the processor.

The libraries available in tensor flow will speed up the computations in this project by at least half the time (Tom Hope, 2017). We can use the OpenCV library implementation of the Cascade classifier. However, upon further trial and error, none of the libraries can be accurately used for this project. Several reasons contribute to this, including the fact that there are libraries available that are remotely similar to the kind of modelling that is suitable for this project. This will be discussed in detail in Chapter 4.

Without these libraries, the only option left was to build a new model specifically for this project (Qiang Zhu, 2006). This includes a lot of processing time and many trials before a proper model could be built. This method is known as “Cascade Training”. The Open CV library is used to detect the spot point at first. Then, images of the positive and negative classes are marked individually. All the positive images are marked with a green box and the negative images are marked with a red box. Each image set has its own xml fine for reference during the modelling.


```xml
<annotation>
	<folder>positive_g</folder>
	<filename>20180410071803.png</filename>
	<path>/mnt/c/dataset/positive_g/20180410071803.png</path>
	<source>
		<database>Unknown</database>
	</source>
	<size>
		<width>320</width>
		<height>240</height>
		<depth>1</depth>
	</size>
	<segmented>0</segmented>
	<object>
		<name>positive</name>
		<pose>Unspecified</pose>
		<truncated>0</truncated>
		<difficult>0</difficult>
		<bndbox>
			<xmin>114</xmin>
			<ymin>27</ymin>
			<xmax>235</xmax>
			<ymax>131</ymax>
		</bndbox>
	</object>
</annotation>
```


Figure 3-18 Image XML File

All images are analysed, and a data file (csv) is created to record them.

filename	width	height	class	xmin	ymin	xmax	ymax
20180410071746.jpg	320	240	positive	133	59	270	204
20180410071803.jpg	320	240	positive	114	27	235	131
20180410071823.jpg	320	240	positive	119	60	227	159
20180410071842.jpg	320	240	positive	110	23	213	122
20180410071907.jpg	320	240	positive	149	25	249	111
20180410071930.jpg	320	240	positive	178	21	274	110
20180410071948.jpg	320	240	positive	119	75	222	166
20180410072002.jpg	320	240	positive	93	35	195	133
20180410072032.jpg	320	240	positive	162	125	260	217
20180410072044.jpg	320	240	positive	50	124	154	227
20180410072058.jpg	320	240	positive	108	138	204	227
20180410072105.jpg	320	240	positive	91	129	181	218
20180410072114.jpg	320	240	positive	91	93	180	175
20180410072128.jpg	320	240	positive	132	96	228	184
20180410072148.jpg	320	240	positive	103	142	196	232
20180410072201.jpg	320	240	positive	206	127	288	215
20180410072212.jpg	320	240	positive	155	67	248	153
20180410072222.jpg	320	240	positive	212	103	304	195
20180410072243.jpg	320	240	positive	79	118	184	206
20180410072252.jpg	320	240	positive	122	79	207	177
20180410072306.jpg	320	240	positive	212	66	304	156

Figure 3-19 CSV Data

1st stage: The cascade model works by first comparing one positive photo to all the negative photos in the file. A vector is formed from this result. Then, the second positive image is compared to all the negative images, a vector is formed from this result (P. Viola, 2001). The resulting vectors are then combined into one vector.

2nd stage:

In the second stage, a blank background of the test piece was added. The positive images are compared to this image to form another vector. This process is known as salting. The differences are further built to increase the accuracy.

3rd stage:

In the third stage, the positive images are compared to random negative images. These negative images are not only based on welding spot points but are also from various other categories. It includes photos of animals such as elephants, tigers, etc., images of vehicles and also fruits. Vector files are formed by comparing the positive images to these images as well. Hence, a broader classification can be formed. This avoids random images being classified as a positive simply because the model does not have a broad comparison. Image of a water droplet for instance, can resemble an image of a spot point in some ways. All of the random images were taken from Google Images.

Finally, all the vector files are combined, and a clear classification is formed for the positive images. In theory, if this learning process is completed successfully, a model with a very high accuracy can be obtained. An accuracy of at least 75% is expected. A probability of a false match can be at a very low level, close to 10^{-5} in some cases. This figure can be seen in some of the existing models that are already built for the OpenCV library. The model for this project was successfully built.

3.5 AI implementation

Before the models are finalized, the learning process is optimized for faster processing speed. In this part, the k-Nearest Neighbour (kNN) algorithm was applied to the existing program.

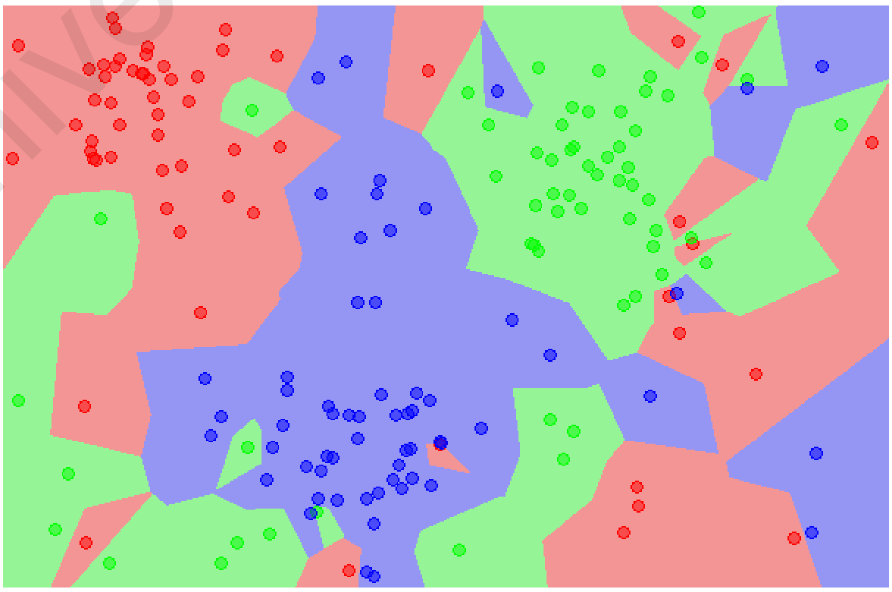


Figure 3-20 k-Nearest Neighbour (kNN) Algorithm *(Mirkes, 2011)*

The algorithm was applied to decrease the positive and negative detection time. This also allows for the program to be used in real time. In kNN algorithm, the prediction attribute of the most similar instances is summarized and then it is used as the prediction for future instances.

The kNN algorithm was only applied after the detection model was working flawlessly. If the model is not working well, the algorithm would not be able to simplify the process. It would then work in a loop while trying to compare the pre-determined selection with the ones in the database. Apart from that, its measured distance would also no be accurate enough to return an accurate output. The kNN is known as a lazy learning because of the fact that the algorithm does not build a model until the time that a prediction is required. It does the work at the last second. When a positive image is tested, it only tests it against positive images and vice versa. It does not have to load the entire model of positive and negative images to output an accurate result. The kNN algorithm shortened the detection program to nearly instantaneous.

The learning algorithm was stopped when the accuracy reached its peak. The main reason for this is to avoid the model from becoming too sensitive. A very sensitive model would look for very minor details in the segments for generalizing. It could look for details that are only present in some positive weld images. As a result, even positive images will be marked as negative. This had happened with a different test program that was modelled before this project. The program begins searching for very small details in a photo of a face that different photos in different angled of the same face were marked as negative instead of positive.

Another reason for this, is to avoid the model from learning the wrong data. If more negative images are fed to the model and it wrongly identifies the negative image as a positive or the positive image as a negative, the model could begin using a wrong set of data for differentiating between positive and negative images.

CHAPTER 4 RESULTS & DISCUSSIONS

4.1 Results

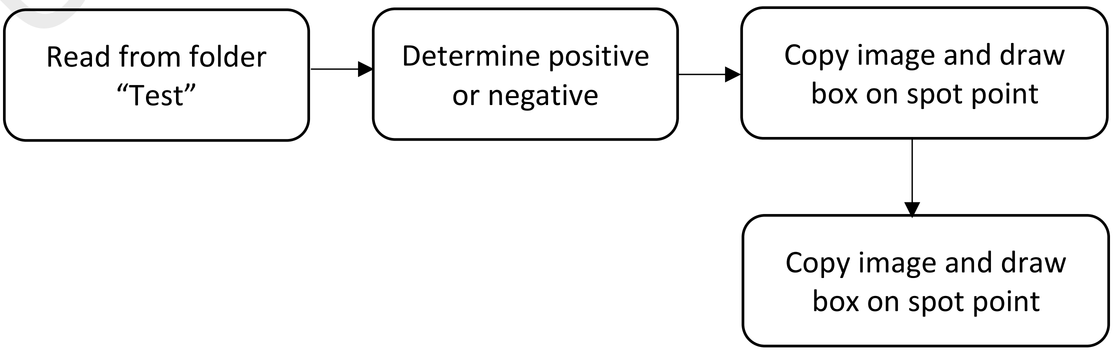
The main concern on the results is the detection of the spot weld quality. The program would be evaluated based on its accuracy in detecting a positive and negative image with positive being the image with a good quality spot point and negative being the image with the bad quality spot point. Extensive testing will be done to evaluate the model and detection execution.

For this stage the procedure for testing would be as following:

1. Copy the test image into the “Test” folder
2. Execute the python3.test.py program
3. The program lists the data in the folder and their results
4. The image is saved into the output folder with the green box for positive and red box for negative image

4.1.1 Detection

The first test was done to evaluate on the detection of images. The program execution works in the following flow:



A positive test image was put into the test folder and the resulting image was saved in the output folder.

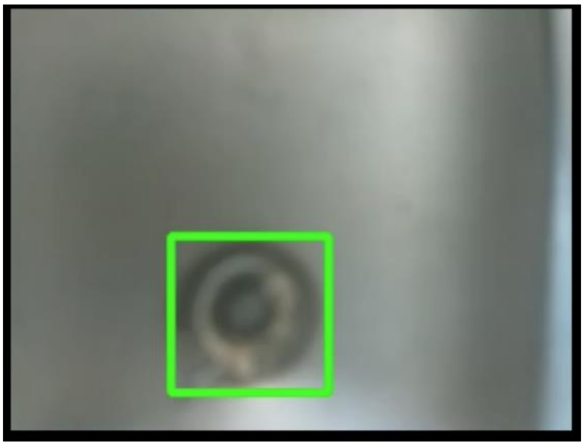


Figure 4-1 Positive Image Test 1

Positive images were put to test to confirm the program. The resulting image was saved in the output folder.

Figure 4-2 Positive Image Test

In the next part, negative images were tested. The resulting images were saved in the output folder.

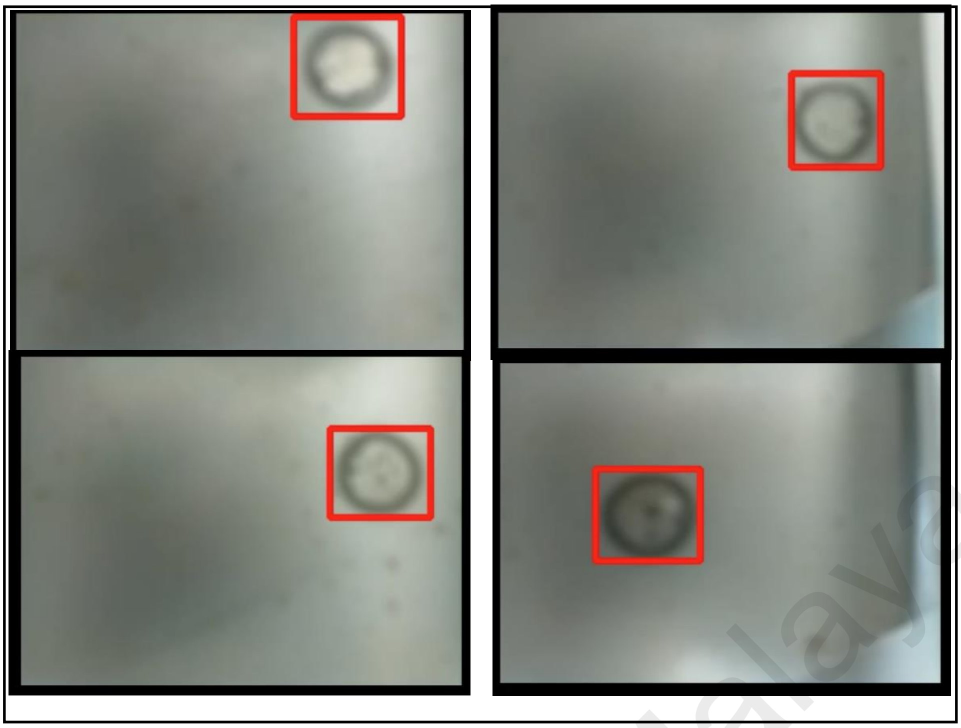


Figure 4-3 Negative Image Test

In the next test, many positive and negative images were put into the test folder in random order and the program was executed. The output folder is displayed below.

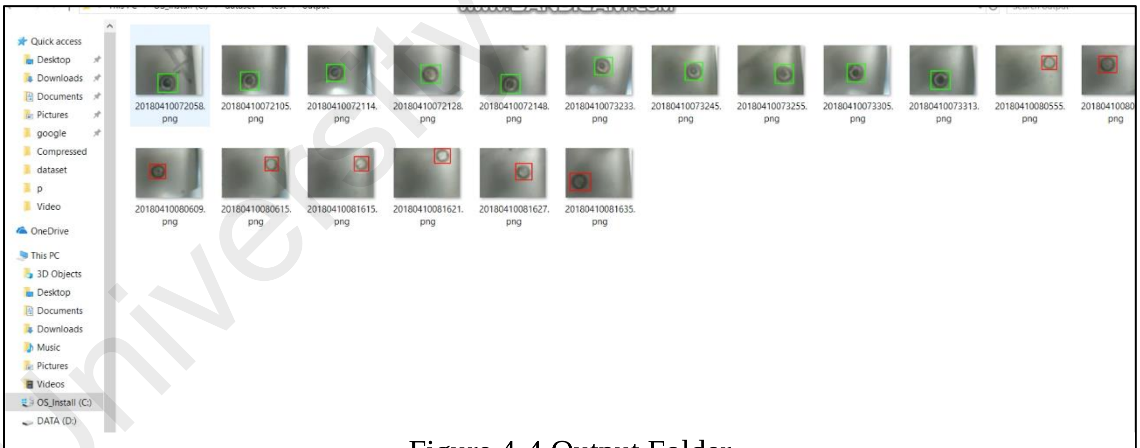
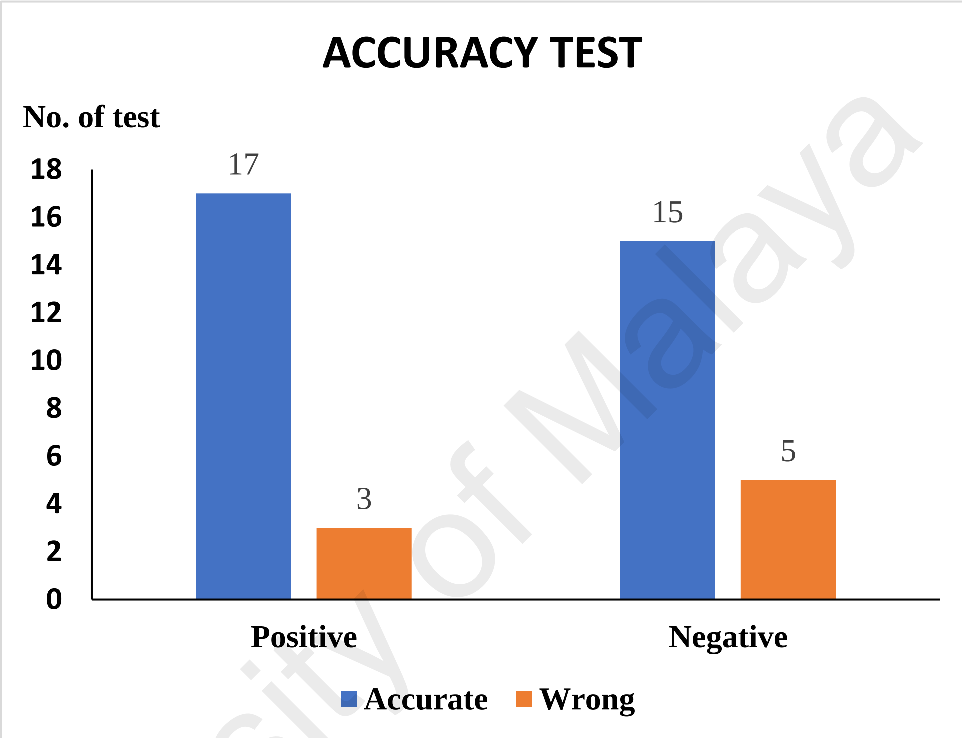


Figure 4-4 Output Folder

The test was also done for images without a spot point. The program drew a red box on one part of the image.

4.1.2 Accuracy

The program was tested many times with negative and positive spot points. The accuracy is used to evaluate the effectiveness of the project. For the individual tests, 20 positive images and 20 negative images were tested. The graph below shows the results of the test.



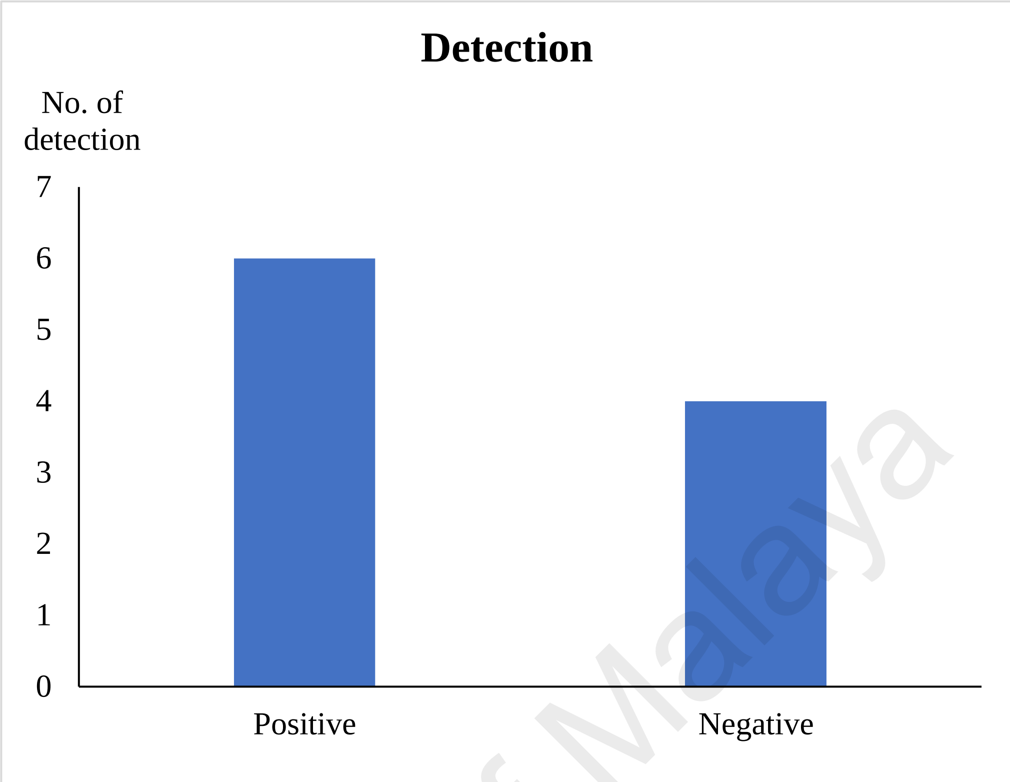
The accuracy of the image detection:

Positive: 85%

Negative: 75%

Marking: 100%

When 10 images were put in the folder, 5 positive and 5 negative, only 1 negative image was detected as a positive image. All images were marked at the spot point correctly.



Accuracy: 90%

Marking: 100%

At 90%, the detection for this model is fairly accurate and the spot point quality can be determined with the image.

The kNN algorithm had significantly dropped the processing power and time needed to process the data. It has also increased the accuracy because it is easier to train with this method. However, more data is needed for extensive accuracy test. Only after more test has been done, the project can be implemented in real world situations.

4.2 Discussion

The main goal of this project is its accuracy. As a matter of fact, the accuracy for any AI related project is expected to be nearly 100%, if not 100%. This is so the machine can replace the human in a certain task. In recent years, the development of AI has been focused in many areas, this includes the medical industry, manufacturing industry, financial sector, war and even space exploration. Accuracy in some industries can make a difference between life and death.

In this project, the accuracy effects the quality of a car. The detection system has to determine the quality of the spot point before the body can move to the next stage. With an 85% - 90% accuracy, the detection program can be used to determine the quality of the spot welding in a car body.

There are several elements that has to be considered before the system is implemented in the industry. The detection program works for the setting mentioned in Chapter 3. However, in the real world, there are many factors to be considered.

1. The material used in every car across many makes and models may be different. Some cars use the same steel material, but it is tempered during the stamping process – hot press stamping process is used to strengthen the steel before it is welded.
2. The same material used for different parts of the car is also used differently. There are a few types used in a car body:
    a. Coated / uncoated
    b. Single layer / double layer / 3 layers
3. The thickness of the material varies largely between the parts of a car, model and make. Thicker parts are used in safety zones in particular. Apart from that, more premium cars use thicker parts for better ride quality and safety.
4. The type of welding machine used will also influence the weld parameters. This includes the welding cable, the gun holder, welding transformer, its cooling system and the welding tip sharpness. Different gun brands have different requirement for their machine. This also results in a different kind of weld pattern.

5. The weld force defers by parts and machine. So, machine apply higher force with higher current.

With so many varying elements, the weld spot will almost constantly look different among vehicle models and makes (Ratna Babu Chinnam, 2006). As a matter of fact, there are many kinds of weld pattern on a single car body. What is considered as a bad weld parameter setting for one part may be the correct setting for a different part. Its real word applications may be much more hard and critical.

Another major factor to consider in this project is the small amount of test data. For a very accurate system, the amount of data would have to be in the thousands and testing will have to be done many times before it can be applied. The data collection and testing phase in this project were limited to the number of test pieces that could be used. Each test piece cost around RM5 – RM9 and this is a significant amount of cost for building the data. For a 1000 spot points, at least 170 test pieces at an estimated cost of RM1,100 would be required for the positive and negative sample data collection. This kind of budget is too much to be allocated for a minor project in the plant.

The sensitivity of such data is also a concern for this project. The weld setting and quality is a protected data for car manufacturers. A simple search on Google would show the criticality of this data. There are almost no available photos of the weld patterns of a spot point in the automotive field. It is almost impossible to get the required permission to make this data available to other researches.

Projects that require images of other subjects such as human faces or human data are even easier to obtain despite being more critical. These kinds of data are available all over the internet and social networks such as Facebook, Instagram, Twitter and other platforms. However, when the subject does not have enough samples, it is simply impossible to accomplish a high accuracy with full detection.

The large amount of data needed with various configurations and the critical issues surrounding the data collection and sharing process possess a huge threat on projects like this.

Another major drawback is with the modelling method. The same method might not be suitable for the different kinds of settings. In many weld settings, the difference between the good and bad spot weld is in the third dimension – the field of depth. The image processing would have to be done with the z-axis included in the vector.

CHAPTER 5 CONCLUSION & FUTURE RECOMMENDATIONS

5.1 Conclusion

This projects proposed a cascade training method with kNN algorithm to identify by marking weld spot points with good and bad quality. The proposed model was tested with sample data and the outputs are marked weld spot points which accurately identify good and bad quality. However, this project has a disadvantage in terms of real world applications. The variation of data or samples simply is not sufficient to build a real working model that can be used in the automotive industry.

Despite this, this project sets the benchmark to a new area in which image processing with AI can be used for the industry. The major role in this model is to provide an AI approach to do the task of determining the quality of a spot weld. The project can be utilized with the right amount of data and variations in terms of weld settings.

5.2 Future Recommendations

This project sets the benchmark for a new field of study. Processes that were manually done before can now be done automatically using a system that utilizes AI. The spot welding quality check is still one of the major concerns in the automotive industry and with proper study, this project can be used to rectify the issue. The following are the recommendations that can be implemented in this project by future research to fully utilize it.

1. Working with welding gun / equipment manufacturers to fully implement the features for all settings

2. Creating a global data set and a library for the spot weld image and specifications in the open source library for further development.
3. Collecting the data with a stereo camera system to obtain a 3-dimensional vector instead of a 2-dimensional vector. This would significantly improve the detection model for welding with other settings.
4. Collaborate with different car manufacturers to determine the effects of each setting on the different kinds of material used in the car.

REFERENCES

Menachem Kimchi, D. H. (2017). *Resistance Spot Welding: Fundamentals and Applications for the Automotive Industry. Synthesis Lectures on Mechanical Engineering.* Morgan & Claypool Publishers.

Li, W. (1999). *Monitoring and diagnosis of resistance spot welding process.* Michigan: University of Michigan.

N. Wylie, S. R.-J.-S. (2009). NDE system for the quality control of spot welding in the automotive industry .

Admin. (2017, April 15). *Resistance Welding : Principle, Types, Application, Advantages and Disadvantages*. Retrieved 3 2, 2018, from mech4study: http://www.mech4study.com/2017/04/resistance-welding-principle-types-application-advantages-and-disadvantages.html

Lai Xinmin, Z. X. (2017). Weld Quality Inspection Based on Online Measured Indentation From Servo Encoder in Resistance Spot Welding. *56*(No 4).

Anbarjafari, G. (2014, January). *Image Processing*. Retrieved March 11, 2018, from UNIVERSITY of TARTU: https://sisu.ut.ee/imageprocessing/book/1

Wikipedia. (2018, April 10). *Artificial intelligence*. Retrieved April 11, 2018, from Wikipedia: https://en.wikipedia.org/wiki/Artificial_intelligence

FOUNDATION, R. P. (2009). *RASPBERRY PI 3 MODEL B*. Retrieved from raspberrypi: https://www.raspberrypi.org/products/raspberry-pi-3-model-b/

Venners, B. (2003, January 13). *The Making of Python*. Retrieved from Artima: https://www.artima.com/intv/pythonP.html

Varun KumarOjha, A. V. (2017). Engineering Applications of Artificial Intelligence. *60*.

Dan Ciresan, U. M. (2012). Multi-column Deep Neural Networks for Image Classification.

Valkov, V. (2017, May 19). *Creating a Neural Network from Scratch—TensorFlow for Hackers (Part IV)*. Retrieved March 23, 2018, from medium: https://medium.com/@curiousily/tensorflow-for-hackers-part-iv-neural-network-from-scratch-1a4f504dfa8

Sayad, D. S. (2018). *K Nearest Neighbors - Classification*. Retrieved April 1, 2018, from saedsayad: http://www.saedsayad.com/k_nearest_neighbors.htm

Shiliang Sun, R. H. (2010). An Adaptive k-Nearest Neighbor Algorithm.

Shweta Taneja, C. G. (2014). An Enhanced K-Nearest Neighbor Algorithm Using Information Gain and Clustering.

Santosh Kumar Dash, M. P. (2016). Image Classification using Data Mining Techniques . *Reeserach Gate*, 161.

McClure, N. (2017). *TensorFlow Machine Learning Cookbook.* Seattle: Packt Publishing Ltd.

Tom Hope, Y. S. (2017). *Learning TensorFlow: A Guide to Building Deep Learning Systems.* Jerusalem: O'Reilly Media, Inc.

P. Viola, M. J. (2001). Rapid object detection using a boosted cascade of simple features. *Computer Vision and Pattern Recognition, IEEE Computer Society Conference* (pp. 511-518). Kauai: IEEE.

Qiang Zhu, S. A.-C.-T. (2006). Fast Human Detection Using a Cascade of Histograms of Oriented Gradients. *IEEE*, 8.

Mirkes, E. (2011). *KNN*. Retrieved from math.le.ac.uk: http://www.math.le.ac.uk/people/ag153/homepage/KNN/KNN3.html

Ratna Babu Chinnam, D. F.-B. (2006). Automotive Manufacturing: Intelligent Resistance Welding. In D. F.-B. Ratna Babu Chinnam, *Computational Intelligence in Automotive Applications* (pp. 219 - 235). Vancouver: IEEE.