WASTE COOKING OIL CLASSIFICATION USING ARTIFICIAL INTELLIGENCE TECHNOLOGY

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FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2020

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

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2020

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WASTE COOKING OIL CLASSIFICATION USING ARTIFICIAL INTELLIGENCE TECHNOLOGY

ABSTRACT

Palm oil – one of the most common edible oil consumed in Malaysia. It is because Malaysia is one of the countries which supply palm oil to the global market and it is cheap to obtain for the consumer in Malaysia. Most of the Malaysian consume it via food preparation such as deep-frying and cooking. However, due to widely available for Malaysians, consumers also lacking awareness in dealing after using the edible oil. Most of the household consumers discard excess waste cooking oil (WCO) into sewage and with courtesy, some of them stored them in containers and sell to NGOs. Fortunately, artisan soap making is getting on-trend in the Malaysian market plus more people are keen to do business online and thus involve more in Do-It-Yourself (DIY) soap making for small businesses. This is an opportunity to promote the WCO to be reused in terms of soap making. Although there is a minority industry taking part in dealing this WCO recycle and reuse, but for this study is to promote all domestic artisan soap makers to realize using vegetarian used WCO is as good as using fresh palm oil. So, to distinguish between WCO into vegetarian used and non-vegetarian used, a simple Artificial Intelligence (A.I.) system is developed to aid them in distinguish WCO. To develop an A.I. system, a few crucial parameters are chosen after performing literature reviews - total iron content and peroxide value (PV). After getting samples and performed characterization on those samples, total iron content does accumulate in the WCO when the WCO is deep-fried with meat products that contain iron in haemoglobin. While PV does increases when the WCO is stored in a container for a long time. For this study, the hypothesis of vegetarians used WCO should be higher PV due to the lacking of iron in the WCO which catalyses the decomposition of hydroperoxide to alkyl radicals by oxidation-reduction mechanism is not applicable. This is due to the WCO's stored life span factor overshadow it. Lastly, for A.I. development, 2 simple hypothesis sets - Perceptron and Multi-layered Perceptron with Back Propagation (MLP-BP) are chosen to compare the accuracy of each model. The reason for choosing simple models is because of limited data points (10 points). Programming on these 2 models via MATLAB software. Validation on both hypothesis sets is performed using cross-validation, "Leave One Out" method and minimal E_{out} is chosen. After performing the development, Perceptron has minimal E_{out}, 0% while MLP-BP has 3%. This is because of Perceptron is the simplest model and minimal overfitting error which can cause deterministic noise on the result. Hence, to improve this study, more data points are recommended so can develop a more robust A.I. system to tackle more complicated situations for the WCO.

Keywords: Waste cooking oil, Artificial Intelligence, Vegetarian, Peroxide value, Iron content.

KLASIFIKASI MINYAK MASAK TERPAKAI DENGAN MENGGUNAKAN TEKNOLOGI KECERDASAN BUATAN

ABSTRAK

Minyak kelapa sawit – minyak masak yang paling ramai digunakan oleh rakyat Malaysia Sebab Malaysia adalah salah satu negara yang membekalkan minyak kelapa sawit ke pasaran dunia oleh it minyak sawit adalah mudah dibeli di Malaysia. Rakyat Malaysia menggunakan minyak sawit untuk memasak makanan yang untuk makan atau untuk dijual sebagai pendapatan sampingan. Namun, minyak terpakai mestilah diuruskan oleh pengguna. Malangnya, ramai rakyat Malaysia membuang minyak terpakai ke dalam sinki atau guna balik minyak terpakai sampai tengik. Oleh itu, tinkdakan tersebut akan membahayakan kesihatan pengunna dan mencemarkan alam sekitar. Tetapi, sabun artisan adalah salah satu tren yang hangat dalam pasaran Malaysia. Rakyat Malaysia membuat sabun dan dijual serperti pandapatan sampingan melalui dalam talian. Oleh itu, ini adalah satu peluang untuk mengingkatkan kesedaran rakyat Malaysia supaya minyak terpakai boleh dikitar semula dan digunakan balik untuk membuat sabun dengan kos yang lebih rendah dan kekal kualiti sabun. Menggunakan minyak terpakai yang dipakai oleh pengguna vegetarian adalah minyak yang boleh membuat sabun yang sama kualiti dengan menggunakan minyak baru. Untuk memudahkan pengguna mengesah minyak terpakai itu adalah dari pengguna vegetarian, sistem kecerdasan buatan kena diperkembangkan dalam kajian ini. Dalam kajian ini, kandungan besi seperti Fe dan “Peroxide Value” adalah ciri-ciri yang penting untuk membuat klasifikasi minyak terpakai. Setelah sampel yang dikumpul dan dikaji dalam makmal, minyak terpakai yang digunakan oleh pengguna vegetarian adalah tiada kandungan besi manakala minyak yang digunakan untuk masak daging, mempunyai kandungan besi. Tetapi, untuk “Peroxide Value” hanya boleh digunakan untuk mengetahui beberapa lama minyak terpakai tersebut disimpan. Semakin lama minyak disimpan, semakin tinggi “Peroxide Value” dalam minyak tersebut.

Seterusnya, dalam pengaturcaraan sistem kecerdasan buatan, dua model sistem kecerdasan buatan digunakan dan dibandingkan ketepatan dalam minyak klasifikasi seperti “Perceptron” dan “Multi-Layered Perceptron-Back-Propagation (MLP-BP)”. Dalam kajian ini, “Perceptron” adalah model yang lebih tepat dalam klasifikasi minyak terpakai (0%) kesilapan berbanding dengan MLP-BP mempunyai 3% kesilapan. Ini sebab struktur “Perceptron” sangat mudah dan kurang kompleks, manakala MLP-BP strukturnya adalah kompleks. Tambahan pula, sebab data yang terhad untuk membangunkan sistem tersebut, struktur yand mudah adalah faedah untuk bagi klasifikasi yang tepat. Oleh itu, untuk meningkatkan kajian ini, lebih banyak data disyorkan sehingga dapat mengembangkan sistem kecerdasan buatan yang lebih mantap dan boleh menangani situasi yang lebih rumit dalam klasifikasi minyak terpakai.

Keywords: Minyak masak terpakai, sistem kecerdasan buatan, vegetarian, Peroxide value, kandungan besi.

ACKNOWLEDGMENTS

First, I would like to appreciate my first supervisor, Ir. Dr. Jegalakshimi A/p Jewaratnam for giving me the opportunity to execute this project, she has given me guidance and advice to deal with many uncertain events during the Movement Control Order to gets the project on progress.

Besides, I also would like to appreciate my second supervisor, Ir. Dr. Chuah Joon Huang who accepted my proposal and join the research project with me. Plus I appreciate his tutor on the Artificial Intelligence course throughout the semester.

Next, I am thankful for my family and friends for aiding me and giving me support for completing this project smoothly.

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbols

%	:	percentage
g	:	gram
kg	:	kilogram
L	:	litre
meq	:	milli-equivalent
mg	:	milligram
mL	:	millilitre
MYR	:	Malaysian Ringgit
^{o}C	:	Degree Celsius

Abbreviations

2D	:	2 Dimensions
A.I.	:	Artificial Intelligence
ANN	:	Artificial Neural Network
AOAC	:	Association of Official Analytical Chemists
APHA	:	American Public Health Association
BP	:	Back-Propagation
EFB	:	Empty Fruit Brunches
E_{in}	:	Error in sample
E_{out}	:	Error out of sample
I_2	:	Iodine
MCO	:	Movement Control Order
MLP	:	Multilayer Perceptron

MPOB	:	Malaysian Palm Oil Board
ND	:	Not detected
NGO	:	Non-Government Organization
RMCO	:	Recovery Movement Control Order
SGD	:	Stochastic Gradient Descent
TPM	:	Total Polar Material
WCO	:	Waste Cooking Oil

LIST OF APPENDICES

CHAPTER 1: BACKGROUND

1.1 Introduction

Malaysia is one of the palm oil exporters to the global market which contributed almost 40% of the global palm oil production. Palm oil nowadays is being used as edible oil, soap manufacturing, and even biodiesel. Such a massive supply of palm oil is why Malaysian consume palm oil as edible cooking oil since it is much cheaper than alternative edible oil such as olive oil, sunflower oil, etc. In 2020, the cheapest for palm oil as cooking oil which only costs MYR 2.50 per kg. Due to many festive seasons and events, Malaysians love to cook many types of food especially deep-fried such as fried bananas, fried chips, fried fish, fried chicken, and even Japanese style fried prawns. Deep-frying needs to use a lot of edible oil to create a well or a pool of heating medium to fry the food into crispy and tasty cooked food.

However, such a high amount of edible oil consumption, Malaysians are well known for reusing the used cooking oil for another batch of cooking or deep-frying to enhance the taste of the food. Furthermore, disposing of the oil to the sewage system is also one of the ways to deal with excessive waste cooking oil (WCO). Therefore, these actions can lead to health hazards and environmental pollution, and energy wastage.

In Malaysia, 3R (Recycle, Reduce and Reuse) on plastic are well known to people such as using biodegradable plastic bags or even reusing them. However, this awareness does not apply to WCO. Fortunately, soap artisan in Malaysia is getting more popular even shopping malls are selling them as gifts and even as a luxury item depending on the price tag and ingredients. A simple saponification process can be done in every household and selling those products online is also one of the trends in Malaysia. Thus, this is an opportunity to propose artisan soap makers to reuse vegetarians used WCO for soap making at a cheaper cost and remain the same quality as using fresh oil.

To distinguish whether the WCO is used by vegetarians or not, for a common household is not an easy task. Although solely depending on historical records from previous WCO users is the easiest way but for unknown source is not possible and needed to be tested with laboratory equipment.

Therefore, developing a system which able to classify the WCO into 2 categories – vegetarian and non-vegetarian WCO is the main purpose of this project.

1.2 Objectives

1. To identify characteristics that can be used to distinguish between vegetarian and non-vegetarian WCO.
2. To perform characterization on sample WCO for use in training and testing of an Artificial Intelligence system.
3. To develop an Artificial Intelligence system for classification of the oils.

1.3 Scope

The scope of this study is where the WCO samples are collected randomly within Selangor districts. It is because of near to University Malaya and no need to cost more on transportation. Besides, WCO is also collected from deep-frying usage only. It is because the main factor for causing excessive used cooking oil is deep-frying foods. Lastly, this study is to develop an Artificial Intelligence system to aid artisan soap makers to distinguish the oils.

1.4 Problem Statement

1. WCO is kept reused for deep-frying until it starts rancid thus post health hazard to consumers.
2. WCO is not being managed properly and gets discarded into the environment or sewage system. Thus it increases the power consumption to treat the sewage by

involving more processing stages to separate the oil and increase the environmental pollution.

3. Sorting WCO according to vegetarian and non-vegetarian are not being developed yet due to the low demand for WCO recycling.
4. Artisan soap makers have problems in distinguishing vegetarian or non-vegetarian oil.

1.5 Significance

The estimated significances of this study are the A.I development can be used for the preliminary sorting system before sending the waste into the sewage processing system. Sorted waste oil is then can be reused for more alternative processes such as biodiesel production, etc. Besides, creating awareness to Malaysians that WCO can be stored and reused for making products such as soaps instead of discarding them. Thus this is to strengthen the oil recycling awareness among Malaysians.

CHAPTER 2: LITERATURE REVIEW

2.1 Lacking Waste Cooking Oil (WCO) Management

In 2015, Malaysia has managed to contribute 39% of the global palm oil production (Ferdous Alam, Er, & Begum, 2015) and it is forecast to produce 20 million tonnes in 2020 (Shankar, 2020). Besides, the domestic consumption palm oil is approximately 4 million tonnes (IndexMundi.com, 2019) as shown in Figure 1. Hence, it is leading to more waste palm oil disposal in the domestic sector. As stated by the Malaysian Sewerage Industry Guidelines a typical untreated domestic sewage contains 50 – 150 mg/L of oil and grease (National Water Services Commission (SPAN), 2009). Currently, in Malaysia there are many commercial practices and undergoing research works to tackle the waste palm oil such as energy recovery from palm oil residue, using Empty Fruit Bunches (EFB) and shell as fuel to generate steam (N. Abdullah & Sulaiman, 2013), pyrolysis of oil palm shell (Huang et al., 2019), and using the EFB compost to form a biofertilizer (Hoe, Sarmidi, Syed Alwee, & Zakaria, 2016).

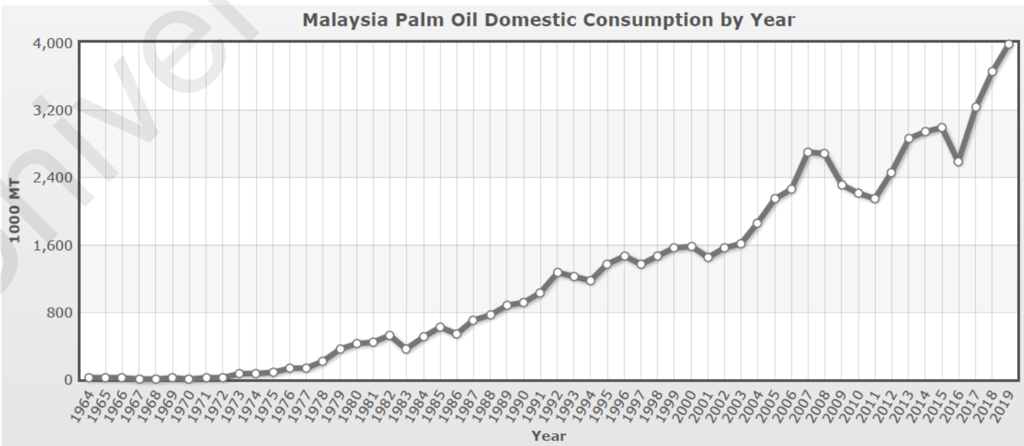

Figure 1 Domestic palm oil consumption in 2019 as a record of 4 million tons. ***(IndexMundi.com, 2019)***

Such advanced research studies and practices as mentioned are mostly targeted in the industries sector to tackle the by-products of edible oil production. However, for waste cooking oil (WCO) management from a household perspective, there is a lacking of knowledge and researches in this field. Previous studies (Kabir, Yacob, & Radam, 2014; Kamilah, Kumar S, & Ay, 2013; Yacob, Kabir, & Radam, 2015) has conducted a preliminary survey and it shows that Malaysian are still lacking awareness in recycling the WCO and lacking on knowledge on dealing with excess used cooking oil other than disposing them into landfill or sewage system. Besides, in Malaysia, the community claimed the best way of conserving the WCO is to reuse it for cooking until it gets rancid (Kamilah et al., 2013). Hence, causing potential health hazard to consumers (A. Abdullah et al., 2015).

Currently, Malaysia has parties such as Alam Flora, Sunway, and other NGOs starting to take part in utilizing the domestic WCO and promote oil recycling to society (Azlee, 2018; biofuels international, 2019; Oon, 2019; Universiti Sains Islam Malaysia, 2019). A recent report from Alam Flora, to attract more people to take part in recycling WCO by offering a reasonable price for consumers to sell their domestic WCO at MYR 1.10 per kg (Oon, 2019). Besides, NGOs also take part in promoting the collecting of WCO from domestic sectors and sending the WCO to local private parties to convert the WCO into other alternatives such as soaps, detergents, and biodiesel (Azlee, 2018; Universiti Sains Islam Malaysia, 2019).

Besides NGOs taking part in recycling and reusing WCO from domestic, a new opportunity on promoting WCO recycling is through home-made soap business. Artisan soap making is trending in Malaysia nowadays as many reports support that Malaysians are willing to spend time to create homemade soaps to get a side income or as a full-time business (Bernama, 2019; Koh, 2017; Leen, 2016; Len, 2019). Homemade soaps mostly use commercially available cooking oil as a soap base product. Hence, soap makers tend to buy fresh oil to make soaps. Thus this can be a new opportunity to promote the soap makers to reuse WCO instead of using fresh oils. Also, a previous report (Maidin et al., 2018) shows that Malaysians are well known in soap making thus they proposed a prototype of a semi-auto soap maker for household usage.

Unfortunately, there are many challenges in promoting domestic WCO recycling to the community. For example, propose artisan soap makers to reuse WCO instead of fresh oils, there are limited published studies on determining the impact of reusing WCO in soap making on health safety and the quality of the soaps. One study found that domestic WCO has minimal impact on soap quality as compared with fresh oils (Thorpe, 2018). Furthermore, the attitude and unwillingness of the community to participate in such recycling activities due to unattractive incentives and troublesome for collection (Yacob et al., 2015).

WCO can be used for many alternative purposes such as biodiesel, reuse for artisan soaps, etc. (Panadare & Rathod, 2015). However, it needs to be sorted out and cleaned properly before they are being used for the next processes. To reuse the WCO for making artisan soaps, sorting the WCO between Halal and non Halal or vegetarian or non-vegetarian is required. A study shows that WCO can develop an undesired scent that inherits from the foods which have cooked by the oil (Thorpe, 2018). Such scent can reduce the quality of the artisan soap products. To minimize the scent side effect, a vegetarian used WCO is preferable to be used for the next processes. To distinguish such WCO, currently, Malaysians rely on historical records of usage of the WCO. Thus this can lead to many adulterated non-vegetarian WCO with it. Besides, wrong information given by WCO providers is also possible due to human errors such as lack of initiative to record the historical oil usage and sort out WCO.

Therefore, to tackle the issues stated above, this study is conducted to investigate and identify parameters to classify WCO between vegetarian and non-vegetarian such as density, viscosity, acid value, etc. After that, developing a preliminary Artificial Intelligence system to aid humans to classify the WCO and this system can be used for the industrial sector and even for domestic purposes.

2.2 Identify Features for Classification of Vegetarian Used WCO.

There are many features or parameters to characterize WCO such as density, viscosity, water content, acid value, iodine value, peroxide value, total polar material (TPM), and iron content. In this section, a brief explanation of choosing the best features to classify the WCO into vegetarian or non-vegetarian used.

2.2.1 Density and Viscosity

Density and viscosity of WCO can vary due to its cooking oil type, temperature, age, and rancidity (Noureddini, Teoh, & Davis Clements, 1992; Ranzi et al., 2018; Sahasrabudhe, Rodriguez-Martinez, O'Meara, & Farkas, 2017). Although increases in density or viscosity of the cooking oil are due to degradation reactions such as hydrolysis, oxidation, and polymerization (Choe & Min, 2007; Sanli, Canakci, & Alptekin, 2011), it still doesn't recognize what kind of foods are being used to deep-fried. Instead, it shows the rancidity of the WCO due to the filterable particles such as crust which left over from the fried foods and burned crisps or carbon accumulated in the WCO. Thus density and viscosity are not selected as features for the A.I. development in this study.

2.2.2 Total Polar Material and Water Content

Total polar material (TPM) represents the accumulation of material which are more polar than triglyceride in the oil. This parameter is quite common to be used as a marker on the rancidity of the WCO (Sanli et al., 2011; Zainal & Isengard, 2010). Although the rate of TPM increases during deep-frying which is because of the hydrolysis of triglyceride into fatty acid. This factor varies, depending on the moisture content and the oil type (Li et al., 2019; Osawa & Gonçalves, 2012; Zainal & Isengard, 2010).

It is because different cooking oil has its fatty acid composition thus affecting the acidity of the oil then affecting the TPM. One study shows that the higher the water content in the WCO, the higher TPM present in the WCO as shown in Figure 2 (Sanli et al., 2011). Besides, the report supports the high water content in the oil, it does promote a higher rate of hydrolysis (Choe & Min, 2007; Osawa & Gonçalves, 2012). But these data do not show what type of oil for each of the samples was collected and the normal temperature is achieved during the cooking.

Temperature does affect the rate of the formation of the polar molecule. Generally, the higher the temperature, the higher rate of reaction. One study shows that even the oil is being heated without any food in it, the rate of formation of TPM is higher (Osawa & Gonçalves, 2012).

Besides that, water content present in the WCO dependent on the food type and how was the food is prepared (Briggs & Wahlqvist, 1984; Osawa & Gonçalves, 2012; U.S. Department of Agriculture, 2020). For example, the average water content in vegetables is higher than poultry or meat so the moisture in the raw food losses into the oil during deep-frying is higher (Boskou, 2010; Choe & Min, 2007; Manjunatha, Ravi, Negi, Raju, & Bawa, 2014; Osawa & Gonçalves, 2012). But these studies did not consider the moisture losses into the ambient. Thus water content in the WCO varies depending on many factors. Therefore, TPM and water content is not preferable for the A.I development in this study.

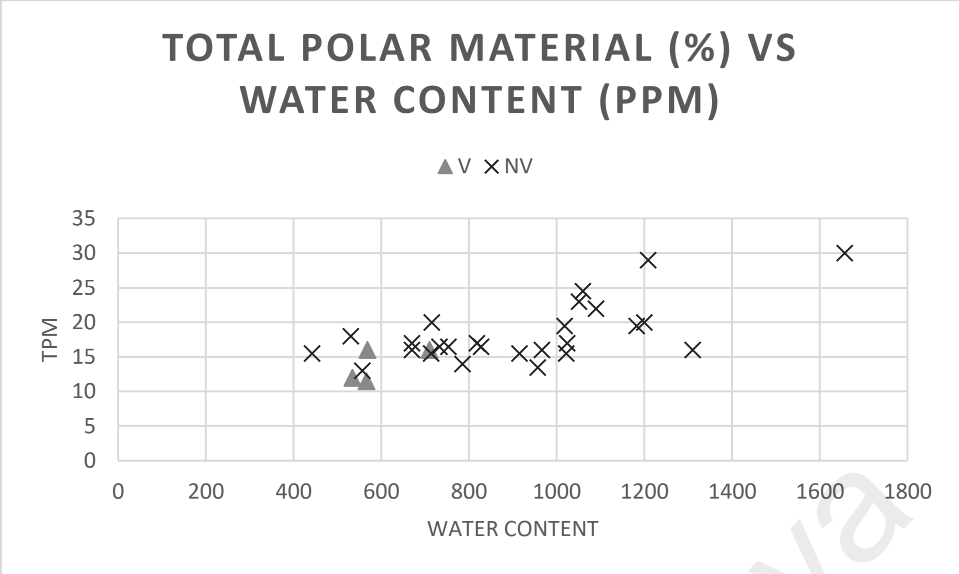

Figure 2: A study of 30 samples from food providers and the tabulated result of TPM against water content. Two classifications, V is vegetarian (pastry restaurants) and NV is non-vegetarian.

2.2.3 Acid Value

As discussed previously, the higher the water content in the oil, the higher rate of hydrolysis of triglyceride into free fatty acid occurs in the deep-frying process (Choe & Min, 2007). This free fatty acid can be measured by acid value. The acid value is defined as the weight (mg) of potassium hydroxide (KOH) required to neutralize the organic acids in 1 g of oil.

Acid value can also be used as a parameter for rancidity (Bordin, Kunitake, Aracava, & Trindade, 2013; Oke, Idowu, Sobukola, Adeyeye, & Akinsola, 2018). Because when the oil being used for deep-frying for a long time, more free fatty acid formed via hydrolysis and accumulated in the oil (Boskou, 2010; Chen, Chiu, Cheng, Hsu, & Kuo, 2013; Choe & Min, 2007; Oke et al., 2018; Park & Kim, 2016; Ranzi et al., 2018; Thorpe, 2018). However, acid values can be different depending on the type of oil. It is because each type of oil has its composition of fatty acids such as palmitic acid, stearic acid, linoleic acid, etc. (Park & Kim, 2016).

Furthermore, according to Figure 3, the same study (Sanli et al., 2011) conducted on 30 samples of used cooking oil, it seems the overall acid value does not correlate with the water content in the oil. Even though some studies claimed the more water content present in the oil, the higher the free fatty acid accumulated in it (Choe & Min, 2007; Osawa & Gonçalves, 2012). This is due to the type of oils those samples are taken, and how long were those oil has been reused are unclear. Therefore, this parameter is not a preferable feature to be used for AI development for this study.

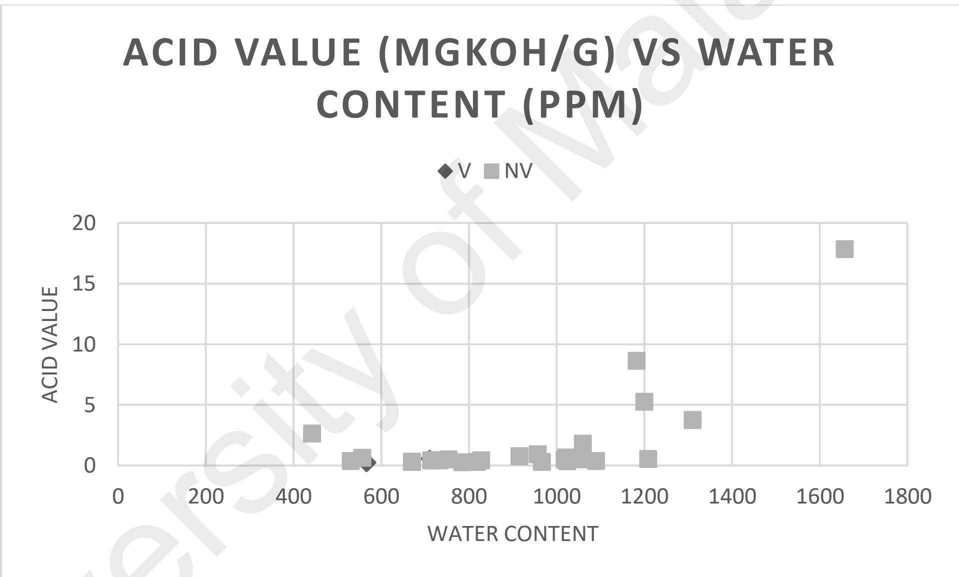

Figure 3: A study of 30 samples from food providers and the tabulated result of acid value against water content.

2.2.4 Iodine Value

Next, iodine value is defined as the amount iodine (I_2) to react with 100 g of oil. It measures the degree of unsaturation of oil. As a higher degree of unsaturation of fatty acid in the oil, the oil easier to gets oxidized due to more unsaturated fatty acid (Bordin et al., 2013; Rasel Molla, 2016).

Cooking oil has its range of composition for fatty acid from mono-saturated to polyunsaturated. Thus it depends on the type of oil (Rasel Molla, 2016; Sanli et al., 2011). Iodine value is used in determining the oxidative stability of the oil which is useful in maintaining the oil quality during the storage.

There are a few factors that affect the iodine value. For example, it decreases after the oil is used for frying as oxidation and hydrolysis occur to disrupt the unsaturated fatty acid (Chebe et al., 2016; Choe & Min, 2007). Iodine value also affected by how the oil being stored. For example, one of the studies shows that the used cooking oil able to sustain its iodine value if the oil is stored in 4^{o}C (Chebe et al., 2016).

The rate of decrement for the iodine value also depends on the type of food. It is because of the moisture contained in the food which can affect the rate of hydrolysis thus further break down the fatty acid into a more stable fatty acid state such as saturated fatty acid (Chebe et al., 2016). As shown in Figure 4, the tabulated data (Sanli et al., 2011) does support the theory as mentioned. However, there are some drawbacks to use this feature to distinguish the WCO between vegetarian and non-vegetarian. For example, the original oil type needs to be known as it depends on its fatty acid composition. The time taken for the WCO has been stored and reused also varies the iodine result. Furthermore, WCO is mixed with other types of cooking oils and giving an unexpected iodine value result. Therefore, iodine value is not a preferable feature for AI development in this study.

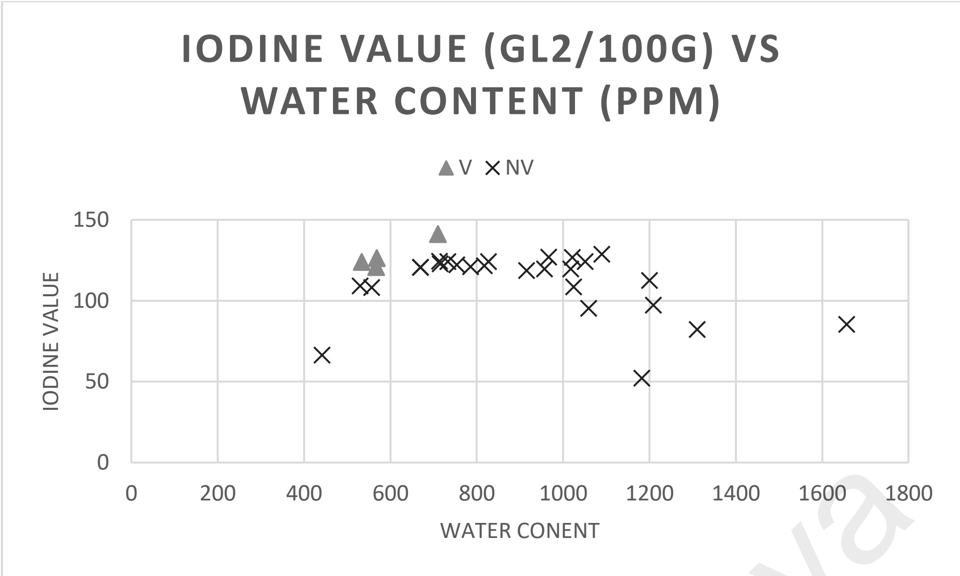

Figure 4: A study of 30 samples from food providers and the tabulated result of iodine value against water content.

2.2.5 Peroxide Value

Next, peroxide value is also one of the most common parameters to determine the rancidity of the WCO (Dermiş, Can, & Doru, 2012; Rasel Molla, 2016). As a standard unit, peroxide value is the milligram equivalent of peroxide contained per kilogram of sample oil. It indicates the extent of oxidation of lipids in the WCO. This can deteriorate the oil's original condition thus causing an “off-flavour” situation for the oil. This oil can post a negative effect on human health after consumption (Dermiş et al., 2012).

In general, peroxide value is used to measure the amount of hydroperoxide accumulated in the WCO. Hydroperoxide is an intermediate compound which caused by many types of lipid oxidations such as auto-oxidation, thermal oxidation, enzymatic oxidation, and photo-oxidation (Choe & Min, 2007; Dermiş et al., 2012; Rasel Molla, 2016). But for deep fat frying, thermal oxidation the most common reaction instead of auto-oxidation (Dermiş et al., 2012). It is because of the moisture evaporation from the food causing a steam blanket between the oil and the atmospheric oxygen in the air. Thus hinders the auto-oxidation (Choe & Min, 2007; Dermiş et al., 2012).

Although, peroxide value varies according to its oil type and the numbers of reused (Chen et al., 2013; Li et al., 2019). However, according to a study (Sanli et al., 2011), peroxide value in WCO is lower for non-vegetarian used as shown in Figure 5. This is due to the presence of metal ions such as copper, iron, and manganese present the oil. Some studies do support that these metals able to reduce the peroxide value by catalysing the decomposition of hydroperoxide to alkyl radicals by an oxidation-reduction mechanism. Furthermore, one of the factors iron accumulation in oil is deep-frying meat (Boskou, 2010; Choe & Min, 2007). Thus peroxide value is a useful feature to distinguish the WCO into non-vegetarian and vegetarian used.

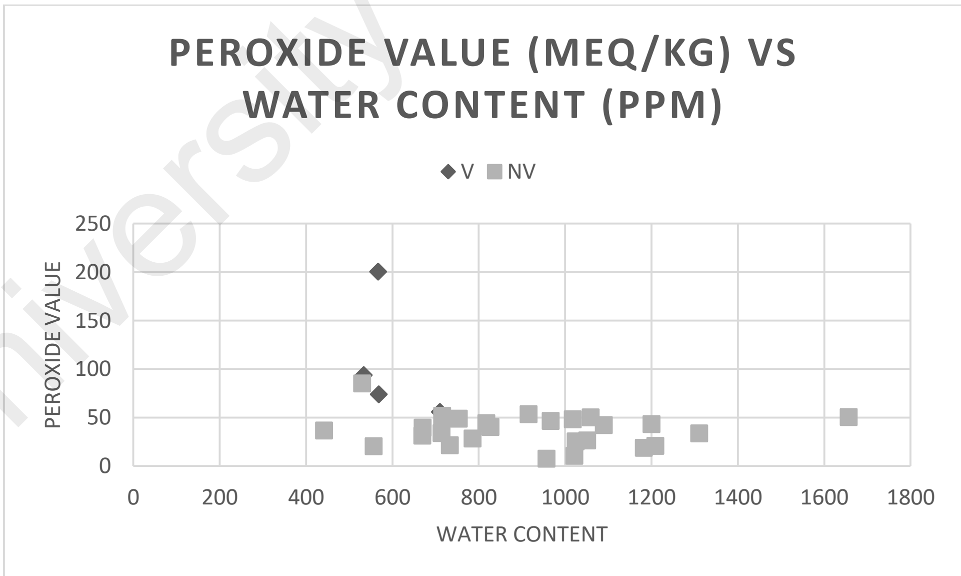

Figure 5: A study of 30 samples from food providers and the tabulated result of peroxide value against water content.

2.2.6 Total Iron Content

Iron is one of the catalysts for the decomposition of hydroperoxide to alkyl radicals via oxidation-reduction reactions. And those iron are mostly due to the denaturation of myoglobin and haemoglobin via high temperature (85 ^{o}C – 200 ^{o}C). Thus releasing the iron into the cooking oil (W. E. Artz, Osidacz, & Coscione, 2005; W. Artz, Osidacz Williamson, & Coscione, 2005).

Mineral loss from the food into the cooking oil was highly debatable since there are reviewers who believe the loss is insignificant due to the mineral content in the food are preserved (Bordin et al., 2013; Boskou, 2010; Oke et al., 2018). But the mineral loss from the food varies depending on what type of cooking method is used (Lombardi-Boccia, Martinez-Dominguez, & Aguzzi, 2002; Pourkhalili, Mirlohi, & Rahimi, 2013).

Many studies also agree that iron accumulation in the cooking oil is possible (W. E. Artz et al., 2005; W. Artz et al., 2005; Boskou, 2010; Choe & Min, 2007). A study has shown that the amount of iron accumulated in the oil is highly dependent on the food which has high iron content such as liver, beef, chicken, etc. Besides, it also depends on how many times the oil has been reused for deep-frying the high iron content food (W. Artz et al., 2005).

According to Table 1, the expected iron content baseline for a WCO is at 0.16 mg/100g of oil. Even though in Malaysia, most of the consumers use palm oil to do deep-frying. Because it is the cheapest cooking oil available in Malaysia, but for this study, a mixed WCO with varieties of oil type is expected from the consumer. Thus the baseline of the iron content must be higher than the fresh palm oil.

In summary, iron accumulation in the WCO is possible for deep-frying and it is due to heme-iron loss from non-vegetarian food (chicken, meat, etc.). Thus, total iron content from the WCO is a preferable feature to be used for A.I. development in this study.

Food Type	Food class	Iron content (mg/100g)	Ref
Corn oil	Oil	0	(U.S. Department of Agriculture, 2020)
Sunflower oil	Oil	0	
Peanut oil	Oil	0.03	
Canola and soybean oil	Oil	0.03	
Coconut oil	Oil	0.05	
Egg white	Egg	0.08	
Palm oil	Oil	0.12	(Saleh, Murray, & Chin, 1988)
Halibut	Fish	0.16	(U.S. Department of Agriculture, 2020)
Vegetable oil	Oil	0.16	
Pork, back-fat	Meat	0.18	
Eggplant	Vegetable	0.23	
Red onion	Vegetable	0.24	
Banana	Fruit	0.26	
Yellow onion	Vegetable	0.28	
Pineapple	Fruit	0.29	
Carrot	Fruit	0.30	
Salmon	Fish	0.38	
Cauliflower	Vegetable	0.42	
Mushroom	Vegetable	0.50	

Pork, belly	Meat	0.52	
Corn	Vegetable	0.52	
Olive oil	Oil	0.56	
Radicchio	Vegetable	0.57	
Pompano	Fish	0.60	
Squid	Shellfish	0.68	
Tuna	Fish	0.77	
Cabbage	Vegetable	0.80	
Red cabbage	Vegetable	0.80	
Pork, ground, fresh	Meat	0.88	
Bean sprouts	Vegetable	0.91	
Herring	Fish	1.10	
Ground chicken	Chicken	1.51	
Clam	Shellfish	1.62	
Garlic	Vegetable	1.70	
Egg	Egg	1.75	
Ground beef	Meat	1.97	
Beef	Meat	2.27	
Beet greens	Vegetable	2.57	
Egg yolk	Egg	2.73	
Tamarind	Herb	2.80	
Seaweed	Vegetable	3.85	
Mussels	Shellfish	3.95	
Oats	Carbo	4.25	
Oyster	Shellfish	4.61	

Table 1: Iron content according to food type.

2.3 Artificial Intelligence (A.I)

2.3.1 Introduction

Artificial intelligence is a system inspired by humans' biological neurons' behaviours working together to perform a task such as classification, recognition, etc. There are many types of A.I. systems such as Convolutional Neural Network, Support Vector Machine, etc. but for this study, Artificial Neural Network (ANN) will be focused and be used due to simplicity and ability to tackle complex problems (K & S, 2014).

2.3.2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is commonly used to deal with realistic problems, not just in research fields but in real-life applications. In the research field, many studies have been using ANN to aid them to perform nonlinear classification (Ishak et al., 2016; K & S, 2014), forecasting (Haryanto, Saputra, Telaumbanua, & Gita, 2020; Shahabi, Khezri, Ahmad, & Zabihi, 2012) and modelling (Pandey, Das, Pan, Leahy, & Kwapinski, 2016; Yuste & Dorado, 2006).

While for industry fields for example food and municipal waste industries are also started to implement ANN to aid them to perform recognition and sorting tasks (Funes, Allouche, Beltrán, & Jiménez, 2015; Gupta, Shree, Hiremath, & Rajendran, 2019). ANN, simply put as a system that consists of numbers of neurons or perceptron, linked from one with another by layers as illustrated in Figure 6.

After an active perceptron sums the products of its weights then it passes the sum through a non-linear transfer function to produce a binary output for the next perceptron (da Silva, Filardi, Pepe, Chaves, & Santos, 2015). As compared with biological neuron behaviour, they are pretty similar. Where the signal impulse from the sensory is detected and it gets transferred from one neuron to another via axons and dendrites. Such impulses trigger the neuron to send an output after the accumulated positive excitatory dominates from the impulses and exceeds the threshold value (Funes et al., 2015).

Furthermore, ANN works like a simplified human brain is because ANN able to learn to be more accurate in performing a certain task by inputting data or information with supervised and non-supervised learning.

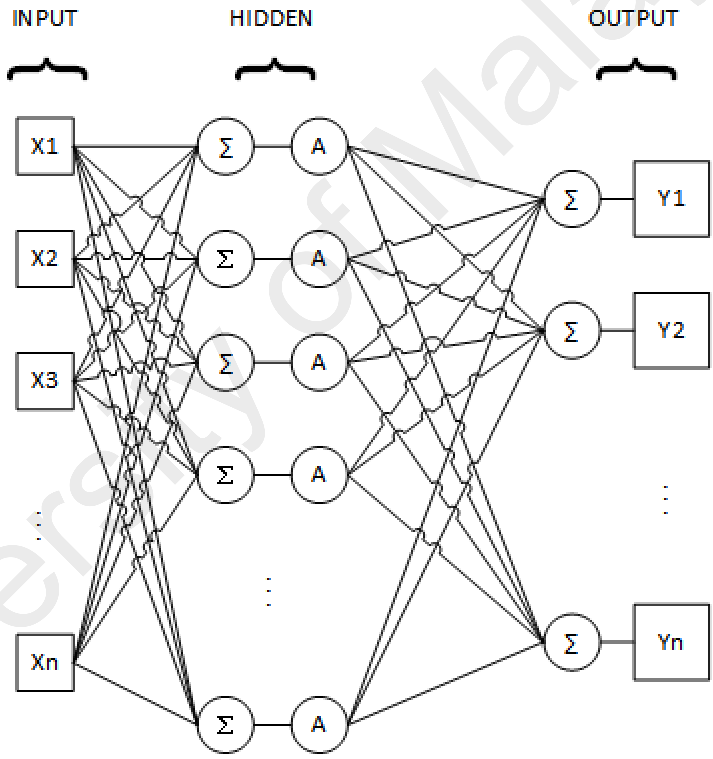

Figure 6: Simplified ANN model structure with n numbers of inputs and outputs.

CHAPTER 3: METHODOLOGY

3.1 Samples Collecting

WCO samples are collected within the Selangor area. Due to uncertain events such as COVID-19 has brought constraints on sample collection and time for completion. Thus only managed 3 source samples where a maximum of 300 mL each. One sample is a vegetarian WCO, while the other two samples are non-vegetarian WCO. The source of the vegetarian WCO sample is from a vegetarian restaurant located in Selangor. While the other two non-vegetarian WCO samples are from a domestic household that is doing an online food provider and it is also located in Selangor.

For the vegetarian WCO sample, according to the manager, those WCO are reused for fried foods and cooking. Limited information is being disclosed regarding the WCO. The manager only disclosed the WCO is palm oil. While the storage period of the WCO and number of times for the WCO being reused are not being disclosed. The sample of the WCO is collected by the manager and claimed the WCO is collected at the top layer. This sample is labelled as “V”, so the rest of the report will be using this name for vegetarian WCO.

Next, there are 2 non-vegetarian WCO samples are collected from the same source. According to the owner, palm oil is the only choice for cooking oil and those collected WCO are from frying meats. There are a variety of meats fried by the same oil such as chicken, beef, fish, and pork. The WCO gets reused once then it gets discarded and stored in a 5 L container. One sample is collected which is labelled as “NVA”, which has been stored in the container for about a month. Meanwhile, another collected non-vegetarian sample which has stored more than 6 months in another 5L container is labelled as “NVB”. For NVA and NVB samples were collected at the top layer of the WCO.

3.2 Characterization of WCO

Again due to the uncertain event such as the COVID-19 outbreak, the University of Malaya laboratory access is prohibited for a while until mid-May. Then the university allows access for research mode only (Wai Ting, 2020). So for this project, outsourcing to laboratory service (Bio Synergy Laboratories Sdn Bhd) is the only choice. Furthermore, due to limited time and limited resources, only able to perform characterization for 10 samples on these 3 source samples. Each sample gets to characterize for peroxide value and total iron content. For 10 samples, 5 samples are from V, 3 samples are from NVA and 2 samples are from NVB. The reason for such distribution is 50% for V and 50% for NV. The testing method for peroxide value is according to MPOB P2.3 (2004) while for total iron content is based on AOAC 999.11 and APHA 3120. The reasons for choosing these testing methods are solely due to limited funds and availability for the laboratory service provided.

3.3 Artificial Neural Network

For this project, since there are 2 features or 2 dimensions are used for the A.I development, a single 2D Perceptron might do the trick but it has a limitation on classification since it obeys Perceptron Convergence Theorem. In other words, if data points are linearly separable as shown in Figure 7, then 2D Perceptron can get the job done within a finite of iterations. But due to limited data points for the A.I development, 2D Perceptron is also used for the development and the result will be compared with MLP-BP.

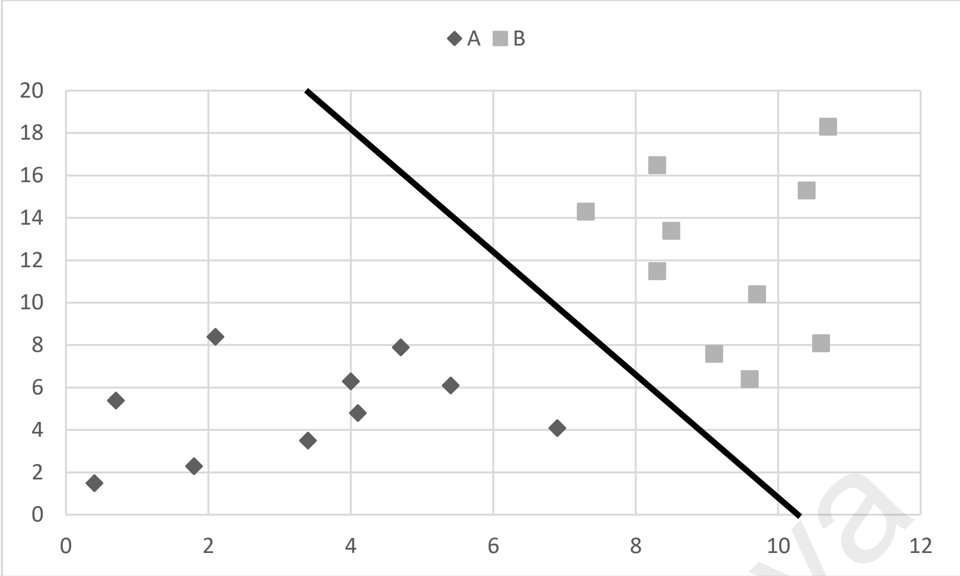

Figure 7: Data points that are linearly separable.

Meanwhile, for Multi-Layer Perceptron with Back-Propagation (MLP-BP), it can tackle linear and non-linear separable data points as shown in Figure 8. However, the accuracy of the classification is depending on the number of degrees of freedom for the MLP-BP or the numbers of hidden nodes and hidden layers in the MLP. So for this project, although limited data points for the A.I development, but MLP-BP also is used and the accuracy of the result is compared with 2D Perceptron.

For the A.I programming, MATLAB software is used for this project due to its license is provided by the University of Malaya and it has machine learning packages such as 2D Perceptron and MLP. This is to minimize programming error thus reduce human error in programming.

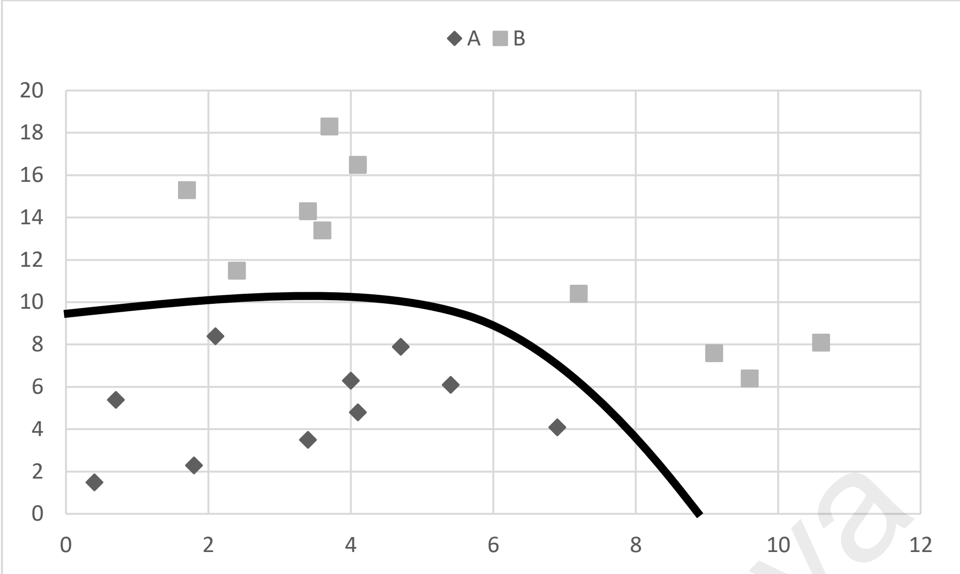

Figure 8: Data points that are non-linearly separable.

3.3.1 ANN Architecture

Again due to limited data points for the A.I development, model selection is limited to minimal complexity. This is to prevent overfitting which can lead to deterministic noise. Therefore for 2D Perceptron, the simple architecture as shown in Figure 9. The first part of the Perceptron is the summation of inputs with respective weights. Weights and bias can be considered as the degree of freedom for tuning the model to reduce errors. Summation equation used for 2D Perceptron as follows:

$$\boldsymbol{S1 = B * W0 + X1 * W1 + X2 * W2} \qquad \textbf{Equation 1}$$

Next is for the activation function for S1, a hard-limit function is chosen since it is a commonly used activation function in MATLAB for Perceptron. The hard-limit function used for the 2D Perceptron as follows:

1. When S1 is greater than 0, then output is 1.
2. When S1 is less than or equal to 0, then output is 0.

Finally, for the learning process, the supervised learning concept is applied. Which means it refers to the reference output for each data point. So, the error must be calculated, and to update the weights to minimize the error.

The equation for calculating the weight differences which links to the error as follows:

$$\boldsymbol{dW = 2 * f'(x) * f(x) * (f(x) - Y)} \qquad \textbf{Equation 2}$$

Then the equation for updating the weights is as follows:

$$\boldsymbol{\begin{pmatrix} W1(t+1) \\ W2(t+1) \end{pmatrix} = \begin{pmatrix} W1(t) \\ W2(t) \end{pmatrix} - lr * \begin{pmatrix} X1 \\ X2 \end{pmatrix} * dW} \qquad \textbf{Equation 3}$$

Where the *lr* is the learning rate and according to the rule of thumb is 0.1.

The final equation for the 2D Perceptron is to update the bias, *W0* as follows:

$$\boldsymbol{W0(t+1) = W0(t) - lr * B * dW} \qquad \textbf{Equation 4}$$

Where *B* is set to 1.

For the in-sample error, the average E_{in} is calculated to check the accuracy of the trained system during training (Abu-Mostafa, 2016d). The calculation as follows:

$$\boldsymbol{E_{in}} = \frac{\sum(\boldsymbol{f}(\boldsymbol{x})-\boldsymbol{Y})}{\boldsymbol{9}} \qquad \textbf{Equation 5}$$

Do note that there are 9 data points were used for training due to "Leave One Out" cross-validation is used for this study.

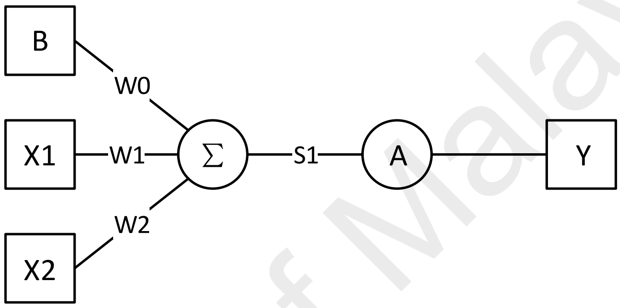

Figure 9: An architecture for 2D Perceptron

Next for the MLP, the architecture is limited to simple form due to limited data points. Therefore as shown in Figure 6, the hidden layer only has 2 layers thus 9 degrees of freedom (6 weights and 3 bias) to tune the system to minimize the error. In MATLAB, the Feed Forward Net function is used and specified it to learn via a well-known Stochastic Gradient Descent (SGD) or BP. The concept of how the MLP works is similar to 2D Perceptron regarding the summation, activation, and average E_{in} calculation. But only weight updates follow the SGD method.

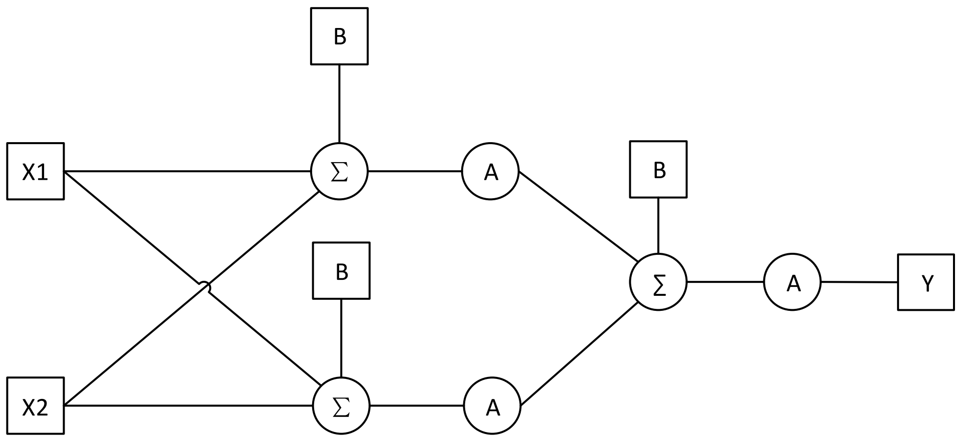

Figure 10: Simplified network architecture for the MLP-BP.

3.3.2 Validation

To measure the system accuracy when the A.I. system applies to the real situation, a "Leave One Out" cross-validation method is applied for this study. For this approach, it was performed manually with a combination of MATLAB and Microsoft Excel. The concept of "Leave One Out" is within 10 points, one point is taken out for testing while the rest are for training. After getting the first E_{out}, then proceed to take another one point out of 10 and is different from the first point repeat the cycle. For example, point 1 is taken out for testing, while the remaining 9 data points are used to do training. After getting the weights and bias or so-called hypotheses set 1, then use point 1 to test and get the error out of sample for point 1, E_{out1}. Then for the next hypotheses set, point 2 is taken out and the rest 9 points generate hypotheses set 2 and get the error out of sample for point 2, E_{out2}. Repeat this until getting all the points to be tested. Then the average of the E_{out} is calculated as follows (Abu-Mostafa, 2016a):

$$\boldsymbol{E_{out,avg} = \frac{1}{10}\sum_{n=1}^{10} E_{out,n}} \qquad \textbf{Equation 6}$$

CHAPTER 4: RESULT AND DISCUSSION

4.1 Introduction

After getting the results from the laboratory, 2 types of models for A.I. systems – 2D Perceptron and MLP-BP are used for training and validate and compare which one has the lowest E_{in} and E_{out}. Lowest E_{in} can be considered as the lowest training error for the system thus the highest accuracy for the system to classify the inputs. While E_{out} is considered as the accuracy for the classification to represent reality situation. So, the best model will be chosen from this chapter and achieve the objective of the study.

4.2 Characterization of WCO

The result for the characterization of 10 WCO samples are collected from the laboratory is shown in Table 2. As mentioned non-vegetarian source WCO should have lower PV due to containing irons (Sanli et al., 2011), but for the current result, this theory does not apply to it. According to Table 2, vegetarian source WCO has lesser PV than non-vegetarian source WCO instead. This is mostly due to the period of storage of the WCO. The longer period of the WCO being stored, the higher the PV. Besides, PV also dependent on ambient temperature during the storage (de ALMEIDA, Viana, Costa, Silva, & Feitosa, 2019). According to the study, the highest increment of PV from its original PV can up to 1500% within 3 months is between 26 – 32 ^{o}C which is a common climate temperature in Malaysia. According to this, it is valid because of NVB has stored more than 3 months while NVA is stored within a month. For V, it is also due to the storage period since the WCO is store on an open container and mix with fresh WCO whenever there are excess from frying foods. Thus, PV for V is lower than the rest.

Next for the total iron content, V contains an insignificant amount of iron content while NVA contains traces of it. This proves that iron is deposited in the WCO due to the iron loss from haemoglobin in meat. Meanwhile for NVB has below detection range which same as V. This might be due to the iron contained in the WCO has sedimented at the bottom of the layer due to prolong storage period. Hence, leaving an insignificant amount of iron content at the top layer. Therefore, NVB has total iron content which below the detection range.

Sample	**PV (meq/kg)**	**Iron (mg/kg)**
V1	9.76	ND (< 0.1)
V2	10.1	ND (< 0.1)
V3	9.61	ND (< 0.1)
V4	9.33	ND (< 0.1)
V5	9.60	ND (< 0.1)
NVA1	15.8	0.6
NVA2	15.3	0.7
NVA3	15.5	0.8
NVB1	40.8	ND (< 0.1)
NVB2	39.9	ND (< 0.1)

Table 2: Results of the WCO characterization for peroxide value and total iron content.

4.3 Artificial Intelligence Development

After getting the results of PV and total iron content as shown in Table 2, these data points are then being used for A.I. development such as training and validation. As mentioned, due to limited data points, the two simplest models are chosen to be used for the development and compare which is the best by choosing the least E_{out} and E_{in}.

As shown in Table 3, 2D Perceptron got zero error instead of a complex MLP-BP model which is having 3% for E_{out} while 1% for E_{in}. This is due to several factors such as the limited data points for the training. MLP-BP can handle multiple degrees of the separation line but to get a decent generalization, a rule of thumb is recommended to be applied. For example, the number of data points is recommended to be 10 times greater or equal to the numbers of effective parameters (weights and bias) that contribute to the model (Abu-Mostafa, 2016b).

The next factor might due to random initialization for the MLP-BP. Initialization is a seed of activation for the gradient descent to locate the minimal. Every time the MLP-BP is executed, the results always vary. Different initialization values used for the weights and bias, different accuracy of the classification result due to the systems locate local minimal instead of global minimal.

Another possible factor for causing the MLP-BP has a lower accuracy than 2D Perceptron for this data set is due to deterministic noise – overfitting due to the complexity of the model and lacking data points for the training (Abu-Mostafa, 2016c).

No. of data point	Perceptron		Multi-layer Perceptron	
	E_{in}	E_{out}	E_{in}	E_{out}
1	0.00	0.00	0.02	0.03
2	0.00	0.00	0.02	0.40
3	0.00	0.00	0.01	-0.00
4	0.00	0.00	0.00	-0.02
5	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	-0.03
7	0.00	0.00	-0.16	0.01
8	0.00	0.00	0.00	0.03
9	0.00	0.00	0.04	-0.08
10	0.00	0.00	0.00	0.00
Average	0.00	0.00	-0.01	0.03

Table 3: Results of in sample error and out of sample error for Perceptron and MLP.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

WCO indeed can be classified between a vegetarian and non-vegetarian used WCO without relying on humans' historical records. As a preliminary study, WCO can be classified using total iron content and PV. Total iron content is the main parameter to be used for the classification while PV is a supportive parameter for the classification. Regarding the PV should be lower for NV than V WCO due to iron acts as a catalyst for the decomposition hypothesis is not applicable for this study. This might be due to the WCO samples collected has a different length of storage period thus affecting the PV. Thus total iron content is the main parameter to distinguish WCO between vegetarian used and non-vegetarian used. Hence one of the objectives has achieved.

Regarding the characterization of WCO, it is obvious that total iron content does affect by the types of food cooked in the WCO. For example, meats with blood are considered non-vegetarian thus causing iron loss from haemoglobin into WCO during deep-frying. Although each oil type has its total iron content. However, in this characterization, they are considered as negligible. Meanwhile, for PV, it is a subjective parameter for distinguishing WCO into vegetarian or not but it can be used to determine the age of the WCO. The length of the WCO stored is longer, the higher of the PV for the WCO. Hence, another objective of this study has achieved.

Last but not least for A.I. system development, again due to limited data points for the system, 2D Perceptron excel in the classification due to its simplicity and minimal overfitting error. While MLP-BP has a slight error for E_{out} which is 3%. This is due to limited data points for the model, initialization values affecting the system to locate the best global minimal and deterministic noise. Hence, according to these results, 2D

Perceptron is the best model for the system to perform classification on WCO into vegetarian or non-vegetarian. Hence, the last objective of this study has achieved.

5.2 Recommendations

1. Increase the number of samples for data points to tackle a variety of conditions and factors in the real situation thus increase the accuracy and getting a better generalization.
2. Increase the number of features for the A.I development to make a more robust system but it will be costly for laboratory tests.
3. Characterization for the Total Iron Content, the units need to be smaller to detect the exact amount of traces of iron content in the WCO such as mg/100g instead of mg/kg.
4. During sampling, the WCO needs to be shaken vigorously to mix the sedimented total iron content at the bottom layer. This is to get an average of the total iron content for the whole WCO in the container instead only at the top layer.

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