Differentiation of Muscle Abnormalities in Turkey Breast Meat in Palestinian Market by Using VIS-NIR Spectroscopy

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نموذج تفويض

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Was successfully defended and approved on 26/05/2019

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Dedication

To

My Parents for being my first teacher…

My sister and brothers for surrounding me and giving me support…

My nephews and neice (Mahmoud, Ahmed and Ayshe), I hope they will grow and read this thesis…

Acknowledgment

First of all, I am thankful to the almighty Allah for granting me good health, strength and peace throughout the research period. I would like to thank everyone who has contributed to accomplish this thesis. I also express my sincere gratitude to my academic supervisor Dr. Nawaf Abu-Khalaf and co-supervisor Dr. Samer Mudalal. I am grateful for their continuous support, patience, motivation, enthusiasm and knowledge. Their guidance helped me all the time of the research, and writing of this thesis that I would never reach on my own.

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الإقرار

أنا الموقع أدناه مقدم الرسالة التي تحمل العنوان:

Differentiation of Muscle Abnormalities in Turkey Breast Meat in Palestinian Market by Using VIS-NIR Spectroscopy

أقر بأن ما اشتملت عليه عليه هذه الرسالة إنما في نتاج جهدي الخاص، باستثناء ما تمت الإشارة إليه حيثما ورد، وأن هذه الرسالة ككل، أو أي جزء منها لم يقدم من قبل لنيل أية درجة علمية أو بحث علمي لدى أي مؤسسة تعليمية أو بحثيه أخرى.

Declaration

The work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree or qualification.

Student's name: Amal Mahmoud Abdullah Zaid اسم الطالبة: أمل محمود عبدالله زيد

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Date:——————————— التاريخ:———————————

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List of Abbreviations

Abbreviation /Notation	Details
WHC	Water- holding capacity
MGA	*Meleagris gallopavo*
kg	Kilogram
PCBS	Palestinian Central Bureau of Statistics
RBC2	Random-bred control
WS	White striping
DPM	*Deep pectoralis myopathy*
PSE	*Pale- Soft-* and- *Exudative*
NIR	Near infrared
VIS	Visible
MVDA	Multivariate data analysis
PCA	Principle component analysis
PLS	Partial least square
MLR	Multiple linear regression
MPLS	Modified partial least- squares
LDA	linear discriminate analyses
SR	Stepwise regression
SMLR	Stepwise multiple linear regression
MSC	Multiplicative scatter correction
SNV	Standard normal variate

1^{st} D	First derivative
2^{nd} D	Second derivative
mm	Millimeter
µm	Micrometer
nm	Nanometer
FWHM	full width at half maximum
CCD	Charged Coupled Device
MH_Z	Mega hertz
A/D	Analog-to- digital
CR	Chroma meter
CIE	Commission Internationale de l'Eclairage
g	Gram
rpm	Round per minute
mM	Millli-molar
STPP	Sodium tripolyphosphate
W	Weight
CP	Crude protein
AOAC	Association of Official Analytical Chemists
$RMSE_p$	Root mean square error of prediction
$RMSE_{cal}$	Root mean square error of calibration
R^2_p	Coefficient of determination in prediction
R^2_{cal}	Coefficient of determination in calibration

SD	Standard deviation
CV	Coefficients of variation
RER	Range error ratio
RE	Relative error

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Abstract

White striping defects in poultry meat is an emerging and growing problem. The main purpose of this study was to employ the reflectance of visible-near infrared (VIS/NIR) spectroscopy to predict and differentiate the quality traits of different levels of white striping defects. Accordingly, 34 out of 60 turkey breast fillets were selected representing a different level of white striping defects (normal, moderate, and severe). Data of VIS-NIR were analyzed by principal component analysis (PCA). It was found that the first principal component (PC1) for VIS, NIR and VIS-NIR region explained 98%, 97% and 96% of the total variation, respectively. PCA showed high performance to

differentiate normal meat from abnormal meat (moderate and severe white striping). Color indexes (L*= lightness, a*= redness and b*= yellowness), pH, marinade uptake, drip loss, cooking loss and chemical composition (moisture, fat, protein and ash) have been evaluated. Our findings showed that prediction models using partial least squares (PLS) were good for color indexes, pH and chemical composition in particular for normal and severe white striped meat. In conclusion, the results of this research showed that VIS-NIR spectroscopy was satisfactory to differentiate normal from severe white striping turkey fillets by using several quality traits.

Key words: White striping, PCA, PLS, VIS-NIR spectroscopy, quality.

1. Introduction

1.1 General Introduction

In the last few decades, tremendous improvements have been achieved growth rate and breast yield of poultry birds, in order to meet the growing demand for poultry meat (Mudalal *et al.*, 2015). Globally, the productivity of poultry meat has been enhanced by intentional genetic selection using traditional quantitative techniques (Zuidhof *et al.*, 2014). The genetic selection was companied by histological and biochemical modifications in the muscular tissues of growing birds (Petracci & Cavani, 2012). It was found that genetically selected birds had low blood capillary vessels density leading to fiber metabolism (Soglia *et al.*, 2018). Accordingly, this was companied by the emergence of several muscle abnormalities such as *Pale Soft Exudative* (PSE) (Petracci *et al.*, 2017), *Deep pectoralis myopathy* (DPM) and the most recent were white striping (WS) and hardening of the breast muscle known as 'wooden breast' (Kuttappan *et al.*, 2017). Moreover, intramuscular connective tissue defects characterized by a loose structure of muscle fiber bundles called 'spaghetti meat', has been recently observed (Maiorano, 2017). The previous poultry meat defects were as a consequence of substantial improvement towards increasing growth rate and breast yield (Petracci *et al.*, 2015).

All previously mentioned defects in turkey and chicken meats (in particular breast meat) are considered as a serious problem to poultry industries because they affected adversely the quality traits of premium cuts. These defects impaired the visual appearance, as well as reduced technological properties, *e.g.* water holding capacity, texture and color. Accordingly, this reflected negatively on consumer acceptance (Kuttappan *et al.*, 2012). The classification systems for affected meat by muscle abnormalities are still based on aesthetic criteria (variations in the color of the meat, whether the meat is too pale or too red, and/or excessive fluid accumulation), could not make an exact judgment to deal with meat quality issues, since it is considered as a subjective method (Barbut, 2009). The affected meat should be culling out from processing line and transformed for further processed meat (such as nuggets and sausages), while the rest of carcass is suitable for human consumption (Brambila *et al.*, 2017).

Differences in meat composition due to increase muscle abnormalities have imposed more pressure on the meat industries to guarantee good meat quality. In relation to production and meat evaluation, there is a need to look for rapid, non-destructive and non-expensive technique.

Over the last years, the use of near-infrared spectroscopy (NIR), in which spectrum with wavelength 700-2500 nm, has increased enormously. As it has appeared that recognition and estimation the number of product contents can be obtained by measuring the amount of NIR radiation that is reflected, absorbed, transmitted and/ or scattered at different wavelengths (Gardner, 2018).

VIS-NIR spectroscopy technique employed to evaluate the chemical composition of meat and meat products (Van Kempen, 2001). It has unique advantages if compared with classical methods, such as quick and frequent measurements and the ease of samples preparation. Moreover, it fits for online applications to assess different quality traits in agriculture field (Abu-Khalaf, 2015; Beghi *et al.,* 2018), pharmaceutical industries (Guillemain *et al.,* 2017) in addition to medical sectors (Monteyne *et al.,* 2018). In another hand, NIR spectroscopy still has some limitations, where there is a necessity for reference method, low sensitivity to minor constituents, as well as the complexity in the calibration (Büning-Pfaue & Hans, 2003).

The ability of NIR spectroscopy to predict several quality traits of meat such as chemical composition (protein, moisture, fat and collagen), pH, water holding capacity, *etc*. have been investigated (Brondum *et al.,* 2000;

Meulemans *et al.*, 2003; Yang *et al.*, 2018; Moran *et al.* 2018). Moreover, the possibility of NIR for classification of meat based on feeding regimes (Cozzolino *et al.*, 2002), strains (McDevitt *et al.*, 2005) and tenderness (Yancey *et al.*, 2010) has been studied.

1.2 Aim

There are no available studies that used VIS-NIR spectroscopy to predict the quality traits of turkey breast meat affected by different levels of white striping. Therefore, the aim of this study is to examine the feasibility of using VIS-NIR spectrometer to detect turkey breast muscle abnormalities in defect samples and predict some chemical parameters in turkey meat.

1.3 Objectives

The objectives of this research are to:

1) Employ VIS-NIR spectroscopy with multivariate data analysis in order to detect turkey breast muscle abnormalities in defect white striping samples.
2) Differentiate different levels of white striping defects.
3) Predict some quality traits in turkey meat.

2. Literature Review: Turkey Meat

In this chapter, the relevant literature is reviewed on the basics of turkey taxonomy and history. The discussion continues with an introduction to meat quality in general and turkey meat in specific. Then it followed with turkey meat production and how to apply this increasing, in addition to an exploration of the muscle abnormalities. Finally, a brief description of consumer and industry challenges.

2.1 Turkey taxonomy and history

According to taxonomy, turkeys are classified in the order of Galliformes of the genus *Meleagris* and Tetraonidae (grouse) family/ subfamily (Banks *et al.*, 1987). The wild turkey is the common name for the *Meleagris gallopavo*, and the forests of North America are native culture (Banks *et al.*, 2006). The female (hen) as in many galliform species is smaller, and if breed/species have a colored feather phenotype (not white) the hen is less colorful than the male (tom or gobbler). There are seven different subspecies of this kind of wild *Meleagris gallopavo*, these are: Rio Grande (*M. g. intermedia*), Mexican (*M. g. gallopavo*), Gould's (*M. g. mexicana*), Eastern (*M. g. silverstris*), Merriam's (*M. g. Merriami*), Florida (*M. g. osceola*) and Moore's (*M. g. oneusta*).

The subspecies distinguished by geographic range and plumage differences. The “turkey” word came after introducing these birds to Europe, at that time, anything foreign was said to be from Turkey and eventually, this word became linked with the species (Crawford, 1992).

2.2 Turkey meat

Meat in its general definition is the flesh of an animal used as food, which composed of tissues, muscle fiber cells, pieces of bones and it also composed of fat connective tissue (Lawrie & Ledward, 2006). Turkey and other poultry like chicken are classified as ‘white’ meat, which is pale color before and after cooking. The most common kind of white or light meat is the lighter colored meat of poultry, coming from the breast, as contrasted with dark meat from the legs (Goldstein & Goldstein, 2006). There are differences in muscle fibers type composition within muscles and between animals *e.g.*, myoglobin variation (Klont *et al.*, 1998). As a result of myoglobin rule as a heme pigment, the existing fiber type profile will result in differences in meat color. Due to these differences, postmortem biochemical processes are affected along with meat quality.

2.3 Turkey meat quality

There are several extrinsic and intrinsic parameters that affect the final quality of the product related to carcass and meat (Guerrero *et al.*, 2017). For instance; breed sex (Galvez *et al.*, 2018), age, animal stress during transport (Carvalho *et al.*, 2018), nutritional status, pre-slaughter conditions, postmortem age and carcass refrigeration rate (Fletcher, 2002). Quality traits considered important for a fresh, healthy turkey meat product are color, texture and water-holding capacity. pH can be considered one of the most important and basic factors that can affect meat quality. Several studies have reported differences in pH between breeds, but it is possibly more related to differences in the pre-slaughter conditions than to their own breed (Lisitsyn *et al.*, 2018). Study based on 15 min postmortem breast muscle pH, for example, tom turkey carcasses were classified as rapid glycolyzing (RG), with pH less than 5.80, or normal glycolyzing (NG), with pH > 6.00 (Rathgeber *et al.*, 1999). Another important attribute that affects consumer purchase is color (Furnols & Guerrero, 2014). Color visual scores, lightness (L*), redness (a*) and yellowness (b*) are the major color parameters used for meat color evaluation (light, normal and/or dark). Colors differences are most likely associated with the myoglobin percentage since the concentration of this pigment has been demonstrated that increases with the animal age, increasing

color intensity. There is a correlation between poultry meat color values and pH (Fletcher, 1999). The distribution and mobility of water in muscle (myowater) *ante*- and *post- mortem* in addition to the intrinsic properties of the water held within the meat could affect and contribute to other fresh meat quality parameters, *e.g.* water holding capacity (WHC), juiciness and tenderness (Pearce *et al.*, 2011).

2.4 Turkey meat production

An increasing in poultry per capita consumption has witnessed in recent years. *Meleagris gallopavo* (MGA) turkey is an important agricultural species that is largely used as a meat type bird. It is the second largest supplier to the globe's poultry meat production after chicken (Scanes, 2007). Turkey production had increased by approximately 104% since 1970, as a result of growing in poultry demand as proteins sources (Patterson *et al.*, 2017).

There has been a major growth in turkey production represented 5.8% of the world poultry meat, in 2009. The average quantity of Palestinian household monthly consumption of poultry and meat was 22.9 kg, where the average consumption of all Palestinian for turkey meat is about 50 tons per day (Palestinian Central Bureau of Statistics (PCBS), 2005).

2.5 Genetic selection

In the past few years, there have been enormous progressions in poultry growth rate and breast yield, in order to achieve high commercial meat production (Mudalal *et al.*, 2015). Thorough changes in poultry industrial productivity have been carried out by intentional genetic selection via traditional quantitative techniques (Zuidhof *et al.*, 2014). Commercially, male turkeys are usually grown to approximately 20 weeks of age with a weight of over 20 kg, this in contrast to the 9 kg of a 3-year-old male wild turkey (Williams, 1981). For example, different changes have taken place in the turkey industry from 1966 through 2003. Total edible carcass yield increased by 6.5 % over this 37 year period. Feed efficiency to 11 kg of body weight for the 2003 toms (2.132 at 98 days of age) was approximately 50% better than for the 1966 random-bred control turkey line (RBC2 toms) *i.e.* (4.208 at 196 days of age). The number of days to reach that weight was halved during that period of time as shown in Figure 1 (Havenstein *et al.*, 2007).

Figure 1. The difference between modern turkeys (right) and RBC2 toms strain established in 1966 and maintained at Ohio State University (Havenstein *et.al.*, 2004).

2.6 Muscle abnormalities

Histological and biochemical modifications due to genetic selection of the muscle tissues have distinctly put more stress on the growing birds (Petracci & Cavani, 2012). Without sufficient capillary support, essential nutrients are unable to be delivered to the muscle and metabolic waste products such as heat and lactic acid will build up in the muscle. This leads to dysfunction in fiber metabolism (Soglia *et al.*, 2018). Accordingly, the emergence of recent breast meat abnormalities such as white striping (WS) and hardening of the breast muscle known as 'wooden breast' (Kuttappan *et al.*, 2017). In addition to deep *pectoral myopathy* (DPM) (Tijare *et al.*, 2016), which also known as 'Oregon disease' or 'green muscle disease', it was first described in 1968 as "degenerative *myopathy*" in turkeys and it was consequently studied at the

Oregon State University, which usually occurs in supracoracoid and it is not related to dietary deficiency or toxicity. Although this condition was first recognized in mature breeder turkeys and broiler breeders, it has become increasingly common in meat birds. In fact, it has been estimated that DPM occurs exclusively in birds that have been selected for high breast meat yield, and its incidence is higher in modern intensive farming systems. It is generally thought that DPM is due to ischemia and increase the growth of muscle in the inelastic sheath. It was found that over the development of supracoracoid is not connected with its blood vessel as shown in Figure 2.

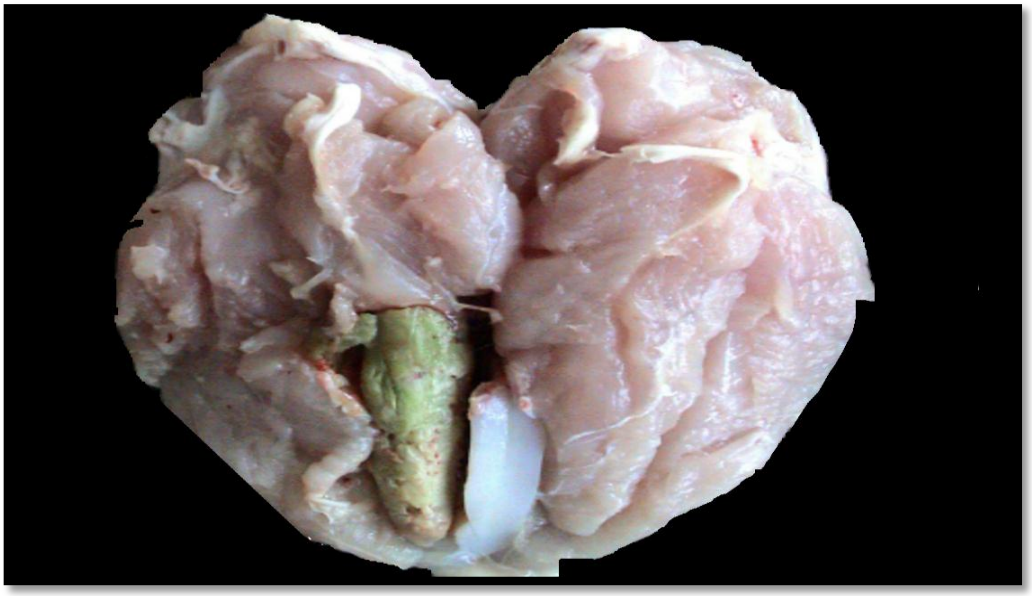

Figure 2. Poultry *deep pectoralis myopathy* (DPM) (Petracci *et al.*, 2015).

Another defect is intramuscular connective tissue defects ‘spaghetti meat’ (Figure 3). Meat affected by this defect is so loose in a structure that the muscle fiber bundles can be pulled away with the fingers (Maiorano, 2017). Finally, *Pale- Soft-* and- *Exudative* (PSE)-like meat (Figure 4). The term PSE was originally described for pork meat, which characterized by light color, flaccid texture and poor water-holding capacity (Petracci *et al.*, 2017). The previous poultry meat defects happen as a consequence of substantial improvement towards increasing growth rate and breast yield (Petracci *et al.*, 2015).

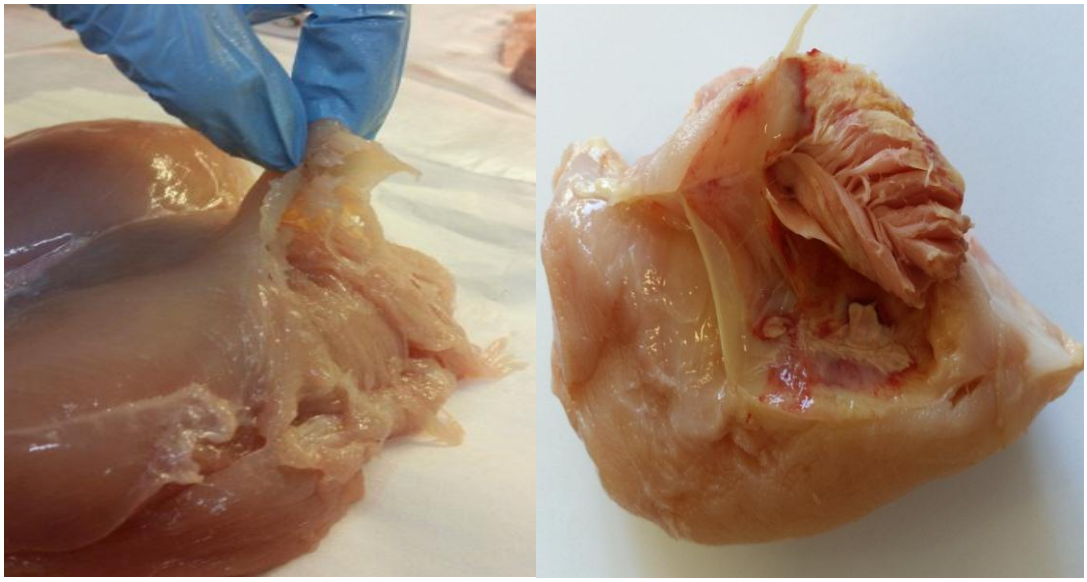

Figure 3. Poultry breast meat with the ‘spaghetti meat’ defect (Maiorano, 2017).

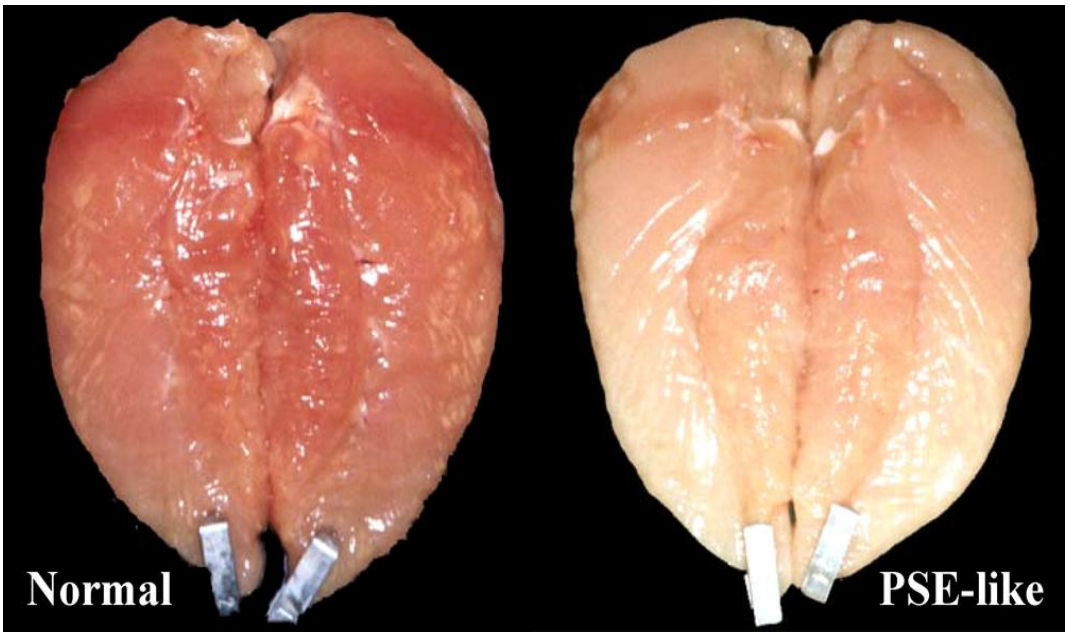

Figure 4. Color differences between normal and PSE- like meat (Petracci & Cavani, 2012).

2.7 Customer and industry challenges

Any changes in physical and/or chemical prosperities in poultry muscles before, during and after the slaughter, will directly affect meat quality. These serious diseases problems on turkey breast meat impaired the visual appearance as well as reduced technological properties, such as water holding capacity, texture and color. This led to downgrading consumer acceptance. In view of the fact that most of the poultry classifying systems around the world are still based on aesthetic criteria (variations in the color of the meat, whether the meat is too pale or too red, and/or excessive fluid accumulation), couldn't make an exact judgment to deal with meat quality issues (Barbut, 2009). Although meat color is known as the most important quality feature to customers, many factors influence its development. Inherently, heme pigment content, color stability and muscle fiber type composition are contributors. Environmentally, temperature, processing techniques and inefficient bleed out can result in abnormal quality. As the occurrence of growth-related abnormalities in turkey breast muscle, the fillet should be culling out from processing line and use them for ground- up products, such as nuggets and sausages, while the rest of carcass is suitable for human consumption (Brambila *et al.*, 2017). The ranges of PSE rate in young turkey breast muscles in the Canadian poultry industry, for example, was found from 18 to 34%,

while in mature turkey hens from 5 to 41% (Barbut, 1996). In the USA, the occurrence range of PSE defect in turkey breast muscles was 30-41% (Owens *et al.*, 2000). Processors have encountered an increasing demand for turkey meat with good quality due to market segmentation. In response to the many specialized markets, the meat industry needs to provide meat based on the quality standards and preferences of every different market. Removing the most valuable part of the carcass during the trimming process cause an obvious reduction in products, this, in turn, incurred significant economic losses (Petracci & Cavani, 2012). On the other hand, several studies showed that these breast defects also affect the chemical composition of poultry meat (*e.g.*, protein content decreases in WS fillets, whereas an increase in fat content as the level of affection increase), thus decrease the nutritional value of the poultry meat (Petracci *et al.*, 2014).

3. Turkey Quality Evaluation

3.1 Methods of turkey meat quality evaluation

The responsibility of poultry plants is mainly to provide their products with good quality to the consumer. Since customers are the final step in the production sequence, it is important to identify which factors affect their behavioral patterns. This would allow the poultry sector to better persuade consumer prospect, demands and needs. Also, it has strongly contributed to the improvement of varied systems of production such as the standard, certified, free-range or organic productions. Turkey meat industries, which produce a different kind of fresh turkey breast meat for local, national or even exporting it to other markets, have to look for a good way to sort the meat into different categories. Therefore, most turkey meat factories have experts to evaluate the quality of meat by different traditional and/or recent methods and techniques. The traditional methods are a sensory evaluation, chemical analysis and microbiological analysis. A new recent advance in the technical sense is optical techniques (Huang *et al.*, 2008).

3.1.1 Sensory evaluation of turkey meat

Expectations of consumers for meat quality grow constantly, which induces the necessity of quality control at the levels of slaughtering, meat cutting and distribution. The sensory evaluation is the oldest method and still used nowadays. It is defined as a scientific method used to evoke, measure, analyze and understand those responses to products perceived using senses of sight, smell, touch, taste and hearing (Stone, 2012). Poultry meat quality factors are typically evaluated by visual inspection from both consumers and specialized meat observers. Even it is relatively fast, such as, "there is no instrument available that has the complexity, style, sensitivity and range of mechanical motions as the mouth or that can quickly change the speed and mode of mastication in response to the sensations received during chewing the meat" (Singham *et al.*, 2015), but it's hard to suitable for a large number of samples. Also, the results are typically very subjective, because of meat's classification different from observer to a group of experts, so evaluation of some quality parameters for the meat fillets such as texture, color, in addition to the water holding capacity subject to human error (Swatland, 2002).

3.1.2 Objective evaluation of meat quality

To overcome the interferences associated with the sensory evaluation and to give a good assessment of meat quality attributes, many objective methods have been developed. These objective tests measure one particular attribute of meat rather than the overall quality of the product. For decades, laboratory analysis has been widely used for meat quality sorting (Mullen, 2002). One of the objective techniques is microbiological analysis, which is habitually applied to detect biological organisms like bacteria or fungi, and to reveal faulty processing methods, as well as testing of deterioration and rancidity, but not so much for identifying other content (Manea *et al.*, 2017). It gives reliable results provided that, for instance, the culture does grow and it is visible, or the sample is not contaminated by some other sources (Nelson & Sperry, 1991). However microbiological analysis must be correlated with sensory testing, but it is time-consuming, expensive than sensory evaluation and it is very tedious. Another traditional technique is chemical analysis. It gives a reliable result about meat quality when the meat samples measured carefully (Andree *et al.*, 2010). Different meat quality measurements, like pH, water holding capacity, protein contents, color and fat contents have commonly been considered as essential elements in meat quality assessment. These attributes cannot be evaluated by sensory or subjective methods only, so meat plants

have been looking for evaluation methods with faster, easier and good precision and accuracy (Mullen, 2002). Chemical analysis can overcome the previous methods limitations but it also has some drawbacks, *e.g.* the need for accurate and correct calibration, the processes may not work correctly due to some substances affect on other results (Singham *et al.*, 2015), if the distribution of the substance in the measured sample is non- uniform maybe will change the result, toxic waste production, in addition, it is considered a destructive method. Due to economic and environmental issues, the number of analysis samples should be limited. It is still time- consuming and not suitable for online measurements.

3.2 Rapid spectroscopic technologies for meat quality evaluation

Differences in meat composition due to increase muscle abnormalities have imposed more pressure on the meat industries to guarantee high meat quality. In relation to production and meat evaluation, there is needed to look for rapid, non-destructive and non-expensive technique (Abasi *et al.*, 2018). Spectroscopic technology is proper for food characteristics and chemical components analysis. This technology includes ultraviolet and visual absorption, fluorescence emission (Karoui, 2018), near-infrared and mid-infrared absorption (Manley & Baeten, 2018), Raman scattering (Gillibert *et*

al., 2018), nuclear magnetic resonance (Fan & Zhang, 2018), microwave absorption (Ekezie *et al.*, 2017) and (ultra)-sound transmission (Damez & Clerjon, 2008).

3.2.1 Visible-near infrared spectroscopy

Visible and near-infrared spectral radiation is defined as emission in the spectral range from 380 nm up to 2500 nm (Figure 5). The visible region is approximately 400–780 nm, while near-infrared region is usually defined by the wavelength range from 780 to 2500 nm (Marten *et al.*, 1989).

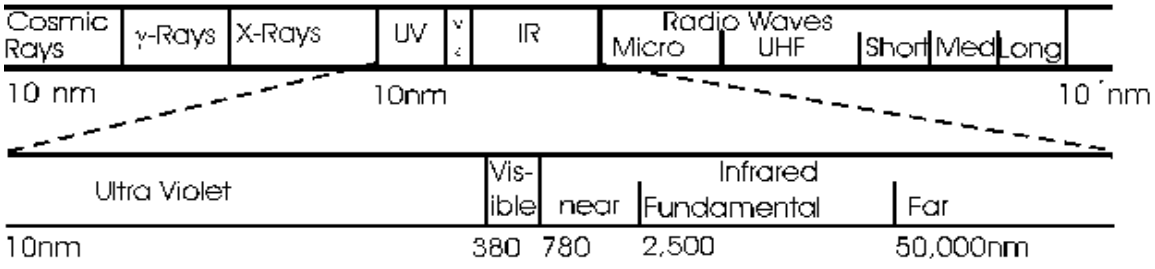

Figure 5. The electromagnetic spectrum and NIR representation (Davies, 2005).

The vibration overtone from chemical bonds, which absorb light energy at specific wavelengths appearing in the visible and near-infrared spectral region, contains an abundance of chemical information. This information can be determined from spectra measured by spectroscopy. The reflectance features of any product in the visible region are recognized by humans as color, which gives information about pigments in the products. In the human grasp, color

directly relates to commodities appearance and quality traits (Abbott, 1999). At room temperature, organic molecules are always in motion that means its covalent bonds are not rigid and behave like flexible springs (bend, twist and stretch). These complicated vibrations can be divided into individual vibrational modes (Figure 6) (Soderberg, 2016). The vibrational energy of molecules is quantized, so when a molecule is exposed to electromagnetic radiation it will absorb energy that matches the frequency of one of its vibrational modes (Coates, 2000).

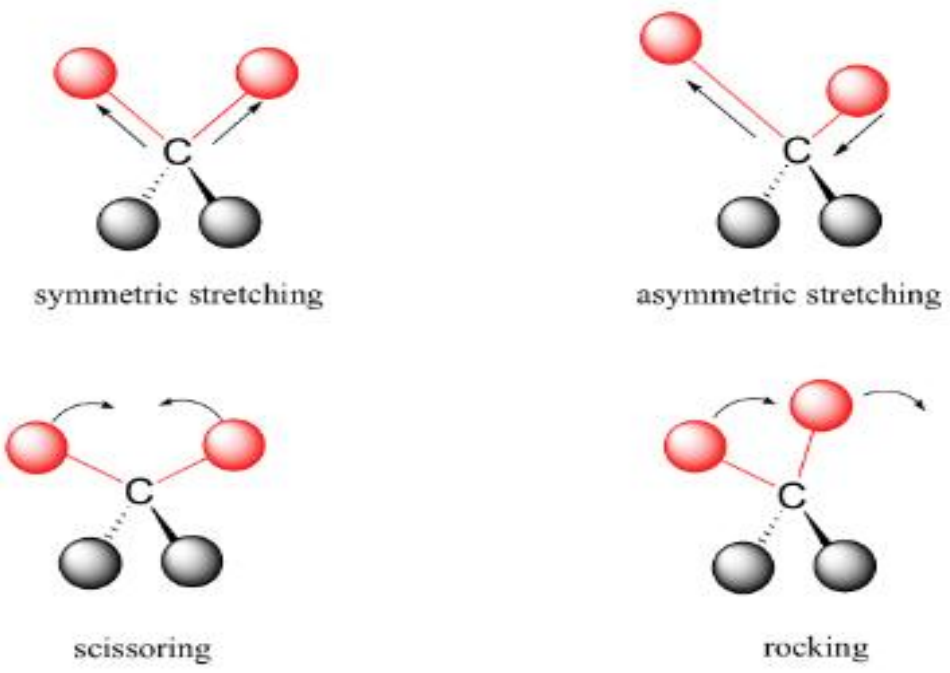

Figure 6. A few types of molecular vibrational modes (Soderberg, 2016).

NIR spectroscopy region is mainly characterized by absorption bands caused by str*etc*hing vibrations of hydrogen (H) bonds with carbon (C) (C-H), oxygen (O) (O-H) or nitrogen (N) (N-H) atoms, in addition to combinations of the essential vibration transitions in the IR region (Parker, 2012). Large changes in vibration state are observed (overtones) in the NIR region and the amount of light absorption is directly increased with the high concentration of the molecules present in the product (Van Kempen, 2001). Molecule's configuration is the key factor for the light frequency used to increase the molecule's vibration. The vibrations between carbon and hydrogen atoms in one molecule, for example, need a light with a different frequency from that required in the same bond in other different molecules. That means each molecule has its own NIR profile or fingerprint, as a result, NIR light can be utilized to identify and quantify materials.

3.2.1.1 Visible-near infrared spectral applications

The history of near-infrared (NIR) begins with Frederick William Herschel in 1800 (Ring, 2000). Over the last years, the use of spectroscopy has increased enormously as it has appeared that recognition and estimation the number of product contents can be obtained by measuring the amount of NIR radiation that is reflected, absorbed, transmitted (Gardner, 2018), and/or scattered at different wavelengths (Figure 7).

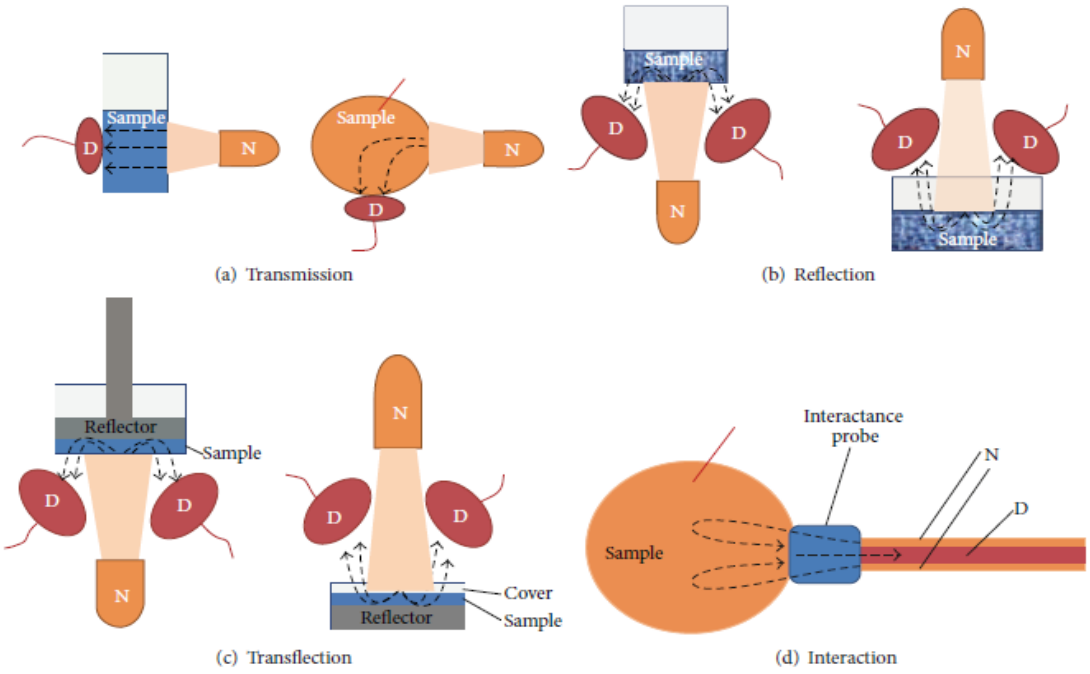

Figure 7. Sample presentation for near-infrared (NIR) spectroscopy. N: NIR light source, D: detector (Alander *et al.*, 2013).

Therefore, NIR spectroscopy has been successfully implemented as a fast at-line and on-line quality control method in many areas of industry. For example, agricultural products and foodstuffs areas lists some of the sectors where NIR technology has succeeded for qualitative and quantitative purposes, such as, grains and seeds (Zhang *et al.*, 2018), livestock and marine products (Bartlett *et al.*, 2018), in addition to fruits and vegetables (Abu-Khalaf, 2015; Beghi *et al.*, 2018), beverage (Genisheva *et al.*, 2018) and other processed food. Moreover, NIR has the ability to assess different quality traits in medical (Monteyne *et al.*, 2018) and pharmaceutical sectors (Guillemain *et al.*, 2017).

3.2.1.2 Visible-near infrared spectral analysis of meat

NIR spectroscopy technique employed to evaluate the chemical composition of meat (ground/ intact) and meat products (Van Kempen, 2001). The ability of NIR to predict several quality traits of meat such as chemical composition (protein, moisture, fat and collagen), pH, water holding capacity, *etc.* have been investigated (Brondum *et al.*, 2000; Meulemans *et al.*, 2003; Moran *et al.*, 2018; Pieszczek *et al.*, 2018; and Yang *et al.*, 2018). Moreover, the possibility of NIR for classification of meat based on feeding regimes (Cozzolino *et al.*, 2002), strains (McDevitt *et al.*, 2005), geographical region and tenderness (Yancey *et al.*, 2010; Su *et al.*, 2012) has been studied.

3.2.1.3 Advantages and limitations of VIS-NIR technique

Visible-near infrared technique has unique advantages if compared with classical methods such as, sample preparation is not required leading to significant reductions in analysis time (dos Santos *et al.*, 2018), non-destructive testing, waste and chemical reagents are minimized, so it is considered as environmentally friendly techniques. In addition, it fits in a wide range for online applications (physical and chemical) and viewing relationships (Manley & Baeten, 2018), which is difficult to observe by other means. It is good to detect hazardous materials since remote sampling is possible (Husnizar *et al.,* 2018). Also, it is suitable even the content is not uniform or solid material such as minerals (Vaudour *et al.*, 2018). In another hand, NIR still has some disadvantages, where there is a necessity for reference method, low sensitivity to minor constituents, optical path must be kept clean and overlapping bands (combination) is not easy to interpret. Also, differences in spectra are often very subtle. As well as the complexity in the calibration (Büning-Pfaue & Hans, 2003).

3.3 Visible-near infrared analysis methods

Responses from spectral data obtained from the samples contain information, which provides details about chemical constituents and the item's nature (Casasent & Chen, 2003). Looking for the best chemometrical or statistical method for data analysis is a very important step to avoid losing information from samples' data. In another hand, Chemometrics is inherently interdisciplinary that fill the gap between different analytical methods such as multivariate statistics, applied mathematics and computer science and their applications in chemistry, biology, biochemistry, medicine, *etc*. These applications play a major and relevant role in spectroscopy and allow identifying and studying the internal relationship between data sets (Burgard, 2018).

2.3.1 Multivariate data analysis (MVDA)

Multivariate data analysis (MVDA) is a powerful technique based on the statistical principle of multivariate statistics, which has observations and analysis of more than one variable outcome at the same time. It tries to reduce the data set and gives an idea about the desired quality parameters (Anderson & Mathematicien, 1958). Different approached have been used for this kind of data analysis, for instance, data mining technique, multiple linear regression

(MLR) was used with principal component analysis (PCA) and showed good discrimination between loins samples subjected to different cooking conditions. González-Mohino *et al.* (2018) and De Marchi *et al.* (2017) applied a modified partial least- squares (MPLS) for sodium (Na) prediction in processed meat products. Also, Geronimo *et al.* (2018) applied PCA to the NIR dataset, followed by linear discriminate analyses (LDA) models for identification and classification of chicken with the wooden breast. In addition to the already mentioned approached, some other different methods have been used for spectral data processing, for example, stepwise regression (SR) (Feng & Sun, 2013), stepwise multiple linear regression (SMLR) (Reis *et al.*, 2018) and partial least squares (PLS) (Wubshet *et al.*, 2018).

2.3.1.1 Principal component analysis (PCA)

Principal component analysis (PCA) is a mathematical procedure for resolving a large set of correlated response variables into principal components (PCs), generating a smaller new set of non-correlated variables whose linear combinations approximate the original data to any desired degree of accuracy (Wold *et al.,* 1987). In other words, the basic idea is to find hidden structures in a dataset to describe these structures. Principal component analysis is commonly used for spectroscopy data analysis to observe the variance

structure of data and visualization of its natural clustering, subsequently multivariate methods (Abdi & Williams, 2010). The data are usually spectra in spectroscopy analysis, and the number of components is equal to or smaller than the number of variables or the number of spectra (Burns & Ciurczak, 2007). In PCA, VIS-NIR spectra represented a bilinear model of the data matrix X. PCs represent in a pattern of observations in plots. The structural part consists of a scores plot, explains the relationship between samples, and a transposed loading plot explains the relationship between variables (Jolliffe, 2011). The major uses of PCA plots are provided descriptive information about the structure of data, rather than inferential (Jolliffe & Cadima, 2016).

3.3.1.2 Partial least squares (PLS)

Partial least squares (PLS) is a well known statistical method which was introduced in the 1960s by the Swedish statistician Herman Wold as an econometric procedure, who then developed it with his son, Svante Wold. Later on, it used by chemical engineers and chemometricians and in other related scientific fields (Wold *et al.*, 2001). PLS is used to find a linear correlation by projecting the predicted variables and the observable variables to a new space. So, PLS is in addition to PCA are called projection methods, because they used to reduce the number of original variables and reject noise

(Legin *et al.*, 2004); instead of finding hyper-planes of maximum variance between response and independent variables. Partial least squares components as mentioned before try to reduce the original X data (spectroscopic data) to a very small number of latent variables, by finding a linear decomposition with Y-data structure (chemical analysis data), whether Y is a single response or multi-response, such that:

$X = TP^T + E$, and $Y = UQ^T + F$, where (2.1)

T = X- scores	U = Y- scores
P = X- loadings	Q = Y- loadings
E = X- residuals	F = Y- residuals

By this way, the decomposition is finalized to increase covariance between T and U (Rosipal & Krämer, 2005). These two types of data are usually organized into two types of matrices, as represented in Figure 8 (Esbensen *et al.*, 2002).

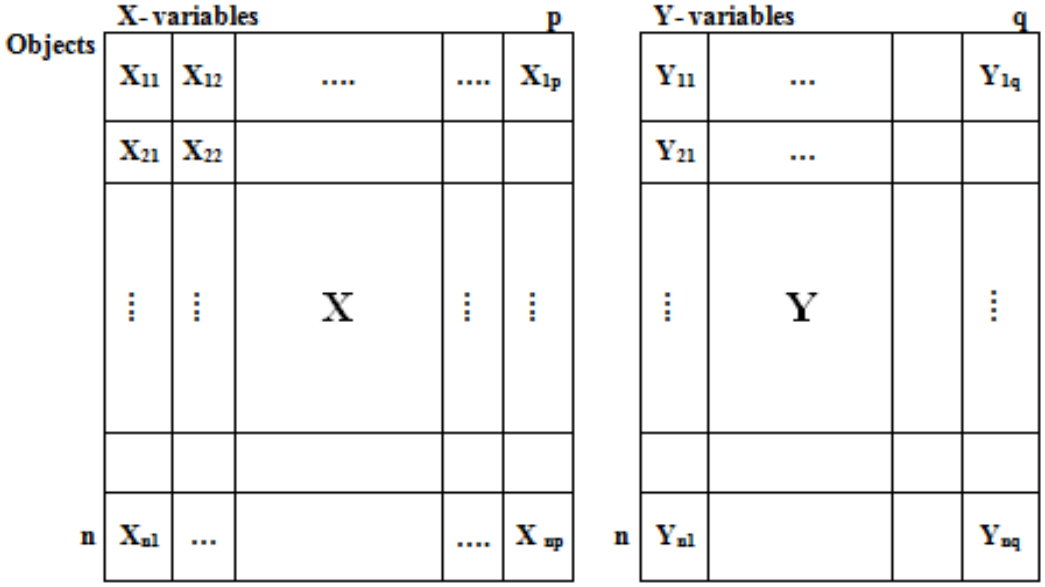

Figure 8: Matrices of the two types of measurments (Esbensen *et al.*, 2002).

3.3.2 Preprocessing

In general, VIS-NIR spectral data are subjected to some long-standing problems due to several reasons, for example, instrument drift, changes in temperature, scatter effects and chemical interferences. These problems cause missing in some spectral data or make them out of range. Also, it leads to a low combination between spectral values. So to obtain more accurate and robust results without non-relevant spectral information VIS-NIR spectral preprocessing data is needed.

Different pre-processing techniques are applied to spectral data to give a good prediction model. These pretreatments are very efficient to eliminated noise, variability and remove some physical phenomena. One of the preprocessing techniques used to improve the following analysis is multiplicative scatter correction (MSC) transformation method (Li & He, 2006). It is used to compensate for additive and/or multiplicative effects in spectral data. Another one is standard normal variate (SNV), which is a mathematical evolution technique of the log (1/R) spectra, it is used to delete slope variation and to correct for scatter effects (Barnes *et al.*, 1989), in addition to first (1^{st} D) and second (2^{nd} D) derivatives. Both of 1^{st} D and 2^{nd} D delete baselines flung and small spectral differences are strengthened. The first and second derivatives are applied using Savitzky–Golay transformation followed with smoothing *(e.g.,* 15-point and second polynomial order) to prevent noise increasing, which is a consequence of derivative. This smoothing is done by the algorithm of Savitzky–Golay, which is a very useful method to effectively remove spectral noise spikes while chemical information can be kept (Rinnan *et al.*, 2009). Finally, baseline correction, which is an essential pretreatment method to the experimental data to reform baseline variations (Rinnan *et al.*, 2009).

3.4 White striping and turkey meat quality evaluation using VIS-NIR reflectance spectroscopy

One of a group of growth-related defects in poultry that has been recently developed in the recent years is White striping (Alnahhas *et al.*, 2016; Kuttappan *et al.,* 2016; Griffin *et al*, 2017).. The appearance of white striation (WS) with variable thickness parallel to the muscle fiber direction is a distinct feature for this defect, commonly occurring in the pectoralis major muscle (Kuttappan *et al.*, 2012; Mudalal *et al.*, 2015). This myopathy negatively affects on the most precious part of a carcass and leads to undesirable nutritional changes (reduce protein content also increase fat and collagen contents) (Mudalal *et al.*, 2015; Bowker & Zhuang, 2016). As a result, it decreases purchase intentions by reducing quality traits. Global attention and different studies towards 'poultry myopathy' in general and 'WS' in particular have increased nowadays (Alnahhas *et al.*, 2016; Zambonelli *et al.*, 2016; Geronimo *et al.*, 2018; and Jiang *et al.*, 2018). Using VIS-NIR technique with its advantages- as mentioned in the previous sections- has increased among poultry industry lines for professionals seeking to enhance meat quality, predict muscles abnormalities and grading the defects degrees (Liu & Chen, 2000; Wold *et al.*, 2018;). There are no studies in the literature concerning the use and assessment non-destructive methods, for instance, NIR spectroscopy

to obtain a more accurate method to classify and predict WS turkey breast meat. This study focused on WS issued related to turkey breast meat production and meat industry. And employ the VIS-NIR method with MVDA for modeling the studied case.

4. Materials and Methods

4.1 Sampling and storage conditions

From local Palestinian slaughterhouse near Tulkarm city (Palestine), more than 60 pectoralis major muscles of 20-week old tom turkey birds were randomly selected based on the appearance of white striations. The evaluation of the presence of white striping was performed on the processing line at 1-2 h of post-mortem after the breast-deboning area. Out 60 pectoralis major muscles, 34 muscles were classified into three groups: normal (free of white striations), moderate (when white striations thickness <1 mm) and severe (when white striations thickness >1 mm) as shown in Figure 9 (Kuttappan *et al.*, 2012). Samples were subjectively pre-selected and pre-classified into categories, packed on ice and transported to Palestine Technical University-Kadoorie (PTUK) laboratory for VIS-NIR measurements. Then they transferred to An-Najah National University laboratories for other quality traits analysis. The pectoralis major muscles were excised from the whole breast muscle. Excessive fat, connective tissue, cartilage and bone fragments were avoided to minimize sampling errors. After 24 h of postmortem, the samples were reclassified again to three categories as previously mentioned to

ensure that each sample is fit to each group because sometimes the thickness of white striation may slightly change during post-mortem time.

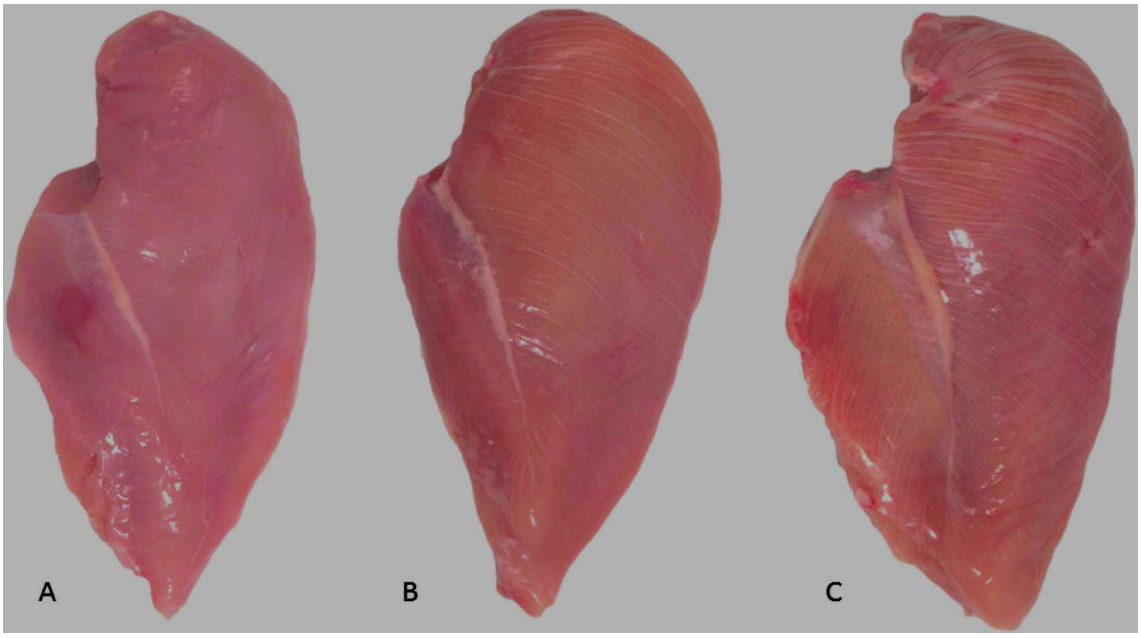

Figure 9. Representative samples of breast fillets with A. normal (no striping), B. moderate and C. severe degrees of white striping (Kuttappan *et al.*, 2012).

4.2. Visible-near infrared spectroscopy measurements

In each turkey breast meat sample (n = 34), three spectra were collected directly on the skin side, in radial section and in tangential section, in a room with a temperature of 23±2˚C and relative humidity of 60%. A USB 2000+ miniature fiber optic spectrometer (Ocean Optics, USA) with a vivo light source and 50 µm fiber optics probe was used for spectra acquisition.

The spectra were obtained at scans with a resolution of 0.35 nm full width at half maximum (FWHM) and spectra range 550-1100 nm. It also has a 2048-element CCD-array detector, 2-MHz analog to digital (A/D) converter, in addition to a high-speed USB 2.0 port. The USB2000+ can be controlled by Spectra Suite software. This device is equipped with an active fan cooling to overcome the risk of sample overheating. The 4 halogen tungsten light sources make the vivo a high-powered VIS-NIR source, which allows a shorter integration time than conventional methods (Ocean Optics, USA). The integration time used in this investigation was 1340 µs. A total of 102 spectra were obtained for turkey samples, and then the average spectra were taken. The VIS-NIR analyses were performed in the diffuse reflectance mode and then recorded as absorbance log (1/R). To ensure the stability of the measurements, a diffuse reflectance standard WS-1 (Ocean Optics, USA) was used as the optical reference standard for the system every five minutes during the experiment. The dark reference was done once at the beginning of each experiment, by closing the entrance of incoming light from probe to the USB2000+ miniature fiber optic spectroscopy using a plastic cap. At the end of all spectral measurements, the acquired data were well stored for later analysis.

4.3 Quality traits analyses

Samples used for VIS-NIR study calibrations (n = 34) were obtained from an unpublished study done at An-Najah National University laboratories. Each fillet was subjected to different proximate chemical composition (moisture content, fat, protein composition and ash) and technological properties (color indexes, pH, drip loss, cooking loss and marinade uptake) measurements.

4.3.1 Color measurements

On the skin-side surface of each fillet from the cranial area, color parameters (L*= lightness, a*= redness and b*= yellowness) were measured in triplicate by the using a Chroma Meter CR-410 (Konica Minolta, Japan) based on the CIE (Commission Internationale de l'Eclairage) system (Internationale de lÉclairage, 1978). The color measurement method is called CIELAB, where L* (lightness) represents the difference between light and dark, a* represents the difference between green and red, while b* represents the difference between yellow and blue as shown in Figure 10.

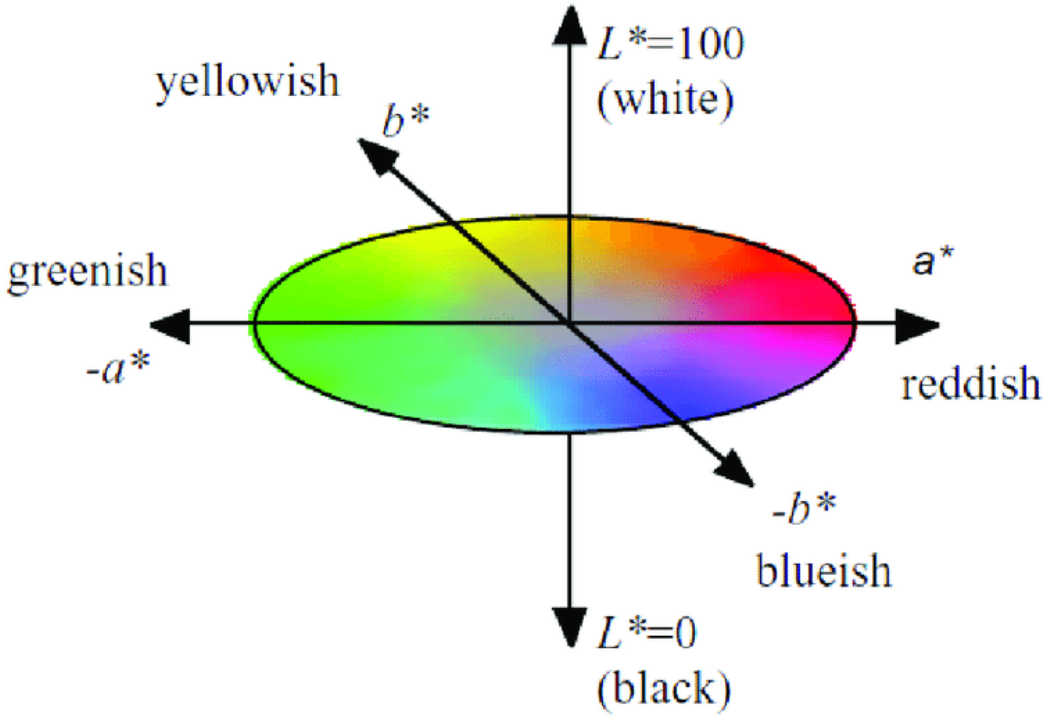

Figure 10. CIELAB color space (Molino *et al.*, 2013).

4.3.2 pH analyses

pH has been measured by using the adopted method described by Jeacocke (1977). (Muscle pH was measured to understand its effect on different quality traits of turkey breast meat. About 2.5 g of meat for each sample was collected from the top of the cranial part as shown in figure 11, minced manually, then homogenized with ultra-turrax for 30 s at speed 10,000 rpm in 25 ml of iodoacetate (5 mM) and potassium chloride (15 mM) solution. The pH of meat suspension was measured by pH-meter calibrated at pH 4.0 and 7.0.

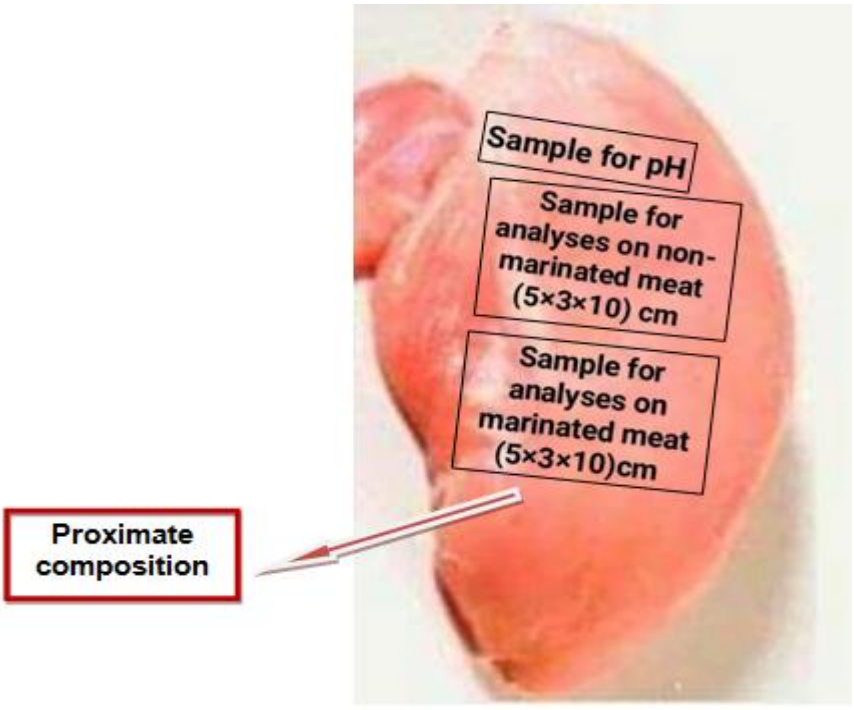

Figure 11. Positions for the determinations of pH, (marinade uptake, drip loss and cook loss) and chemical composition (moisture, protein, fat and ash) in the pectoralis major muscle of the turkey breast meat (Mazzoni *et al.*, 2015).

4.3.3 Marinated and non-marinated meat cuts

From each fillet, a cut (10 × 5× 3 cm) has been excised from the cranial area to evaluate marinade uptake, drip loss and cooking loss.

4.3.3.1 Marinade uptake

Marination and tumbling have been carried out for all meat samples belong for three groups by using a small-scale vacuum tumbler (model MGH-20, Vakona Qualitat, Lienen, Germany) for 25 min (speed 20 rpm, 500 rounds) at pressure -0.95 bar. The marinade solution was added to obtain 1.5% of sodium chloride and 0.4% sodium tripolyphosphate (STPP) in finished product after marination. Marinade uptake was calculated based on meat cuts weight before marination (W_1) and its weight after marination (W_2), according to the equation:

$$\textit{Marinade uptake (\%)} = [(W_2 - W_1)/ W_1] \times 100\% \qquad (4.1)$$

4.3.3.2 Drip loss

After the previous step, the samples have been stored in refrigerator at 2˚C to 4˚C for 48 h, then the weights have been recorded (W_2) to calculate drip loss as the following equation:

$$\textit{Drip Loss (\%)} = (W1 - W2)/ (W1) \times 100\% \qquad (4.2)$$

4.3.3.3 Cooking loss

After 48 h from calculating drip loss percent, samples were vacuumed, packaged and cooked in water bath at 80°C for 24 min until the internal temperature reached 80°C. Finally, the meat samples were removed from bags and reweighed to measure cook loss, according to the following equation:

$$Cooking\ loss\ \% = \frac{Weight\ of\ sample\ after\ storage - Weight\ of\ sample\ after\ cooking}{Weight\ of\ sample\ after\ storage} \times 100\% \quad (4.3)$$

4.3.4 Proximate chemical composition

Different proximate chemical compositions were calculated for the remnant part of the fillets after minced, to have a homogenous mass.

4.3.4.1 Moisture content

The moisture content for raw turkey breast meat was measured according to AOAC official methods (Helrick, 1990), as the following equation:

$$Moisture\ (\%) = ((initial\ weight - dry\ weight)/\ initial\ weight) \times 100\% \quad (4.4)$$

4.3.4.2 Crude protein (CP) determination

The crude protein (CP) was determined according to the official procedure reported by the Kjeldahl method (Jones Jr, 1991), it is an official method described in AOAC (1990) normative. This is used to determine the nitrogen content in organic and inorganic samples, through three major steps: first, digestion (organic nitrogen is converted into NH_4^+), second, distillation (NH_3 is distilled and retained in a receiver vessel), finally, titration (nitrogen is determined).

After applying the previous three phases on minced turkey breast meat protein content was obtained multiplying the concentration of nitrogen by the conversion factor of 6.25 (calculated for meat and meat product) and expressed as a percentage in the below equations, where N represents normality:

$$Nitrogen\ \% = \frac{(ml\ of\ acid\ for\ sample\ acid - ml\ of\ acid\ for\ blank\ ) \times N\ of\ acid\ \times 1.4007}{Weight\ of\ sample\ in\ gram} \times 100\% \quad (4.5)$$

$$Protein\ \% = Nitrogen\ \% \times Conversion\ factor \quad (4.6)$$

4.3.4.3 Crude fat determination

One of the most aspects of meat processing and production is fat content. Turkey breast meat cuts were subjected to the standard method for crude fat determination called “Soxhlet” method (Helrick, 1990).

This method recognized by AOAC. After following Soxhlet method steps, this presented in Figure 12. The percentage of fat content was calculated as the next equation:

$$Crude\ fat\ \% = \frac{Weight\ of\ fat}{Weight\ of\ sample} \times 100\% \qquad (4.7)$$

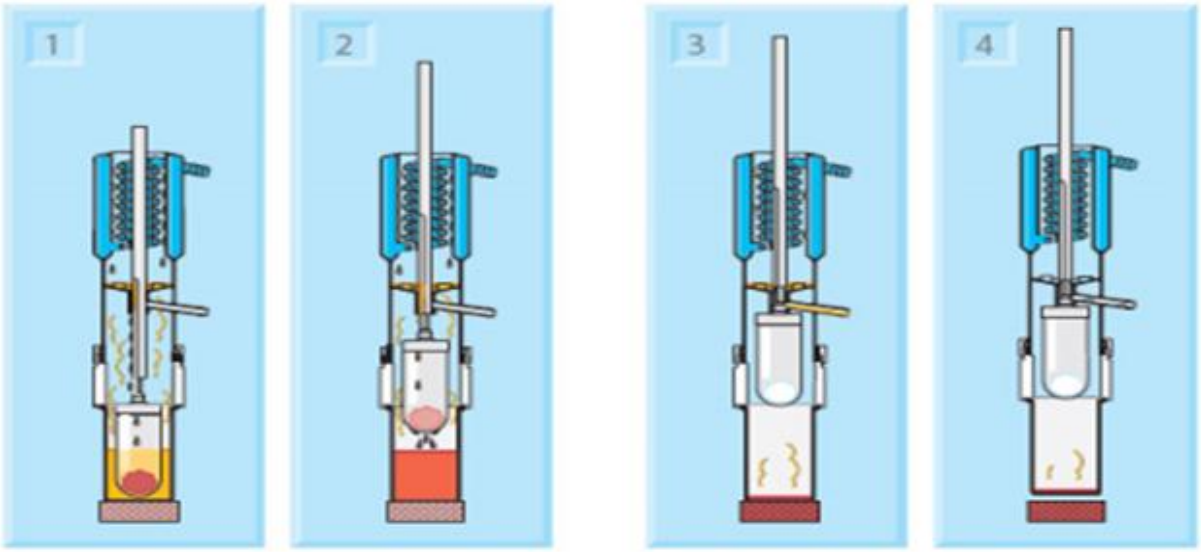

Figure 12. Different fat extraction steps by modern automated Soxhlet extractor (*Analytical Solution for Food Analysis and Quality Control- FOSS, 2017).*

1. Boiling
   Rapid solubilization in boiling solvent
2. Rinsing
   Efficient removal of remaining soluble matter.
3. Recovery
   Automatic collection of distilled solvent for re-uses.
4. Auto-shut down
   The system closes down and the cups are lifted from the hot plate.

4.3.4.4 Total ash contents

Dry ashing procedure was chosen to measure the total amount of minerals in the breast meat. Meat cut sample was heated in a muffle furnace at 525˚C for one hour then cooled in desiccators. About 5 g of finely minced meat was accurately weighted in the ashing dish. After that, the sample was dried in an air oven at 102˚C for two hours. The sample was well-cooked in a muffle furnace at 200˚C and then followed by charring step at 525˚C for 4 h, after the samples have been cooled to 200˚C, moved to desiccators for cooling at room temperature. The turkey meat cut sample was weighed before and after ashing to determine the concentration of ash present. The percentage of ash content can be measured on a wet basis as the following equation:

$$Ash\ (wet\ basis)\% = \frac{Mass\ of\ the\ ashed\ sample}{Mass\ of\ the\ \ wet\ sample} \times 100\% \qquad (4.8)$$

4.4 Data processing and statistical analysis

4.4.1 Spectral analysis

The Unscrambler program (version 9.7, CAMO Software AS, Oslo, Norway) was used for both PCA and PLS.

4.4.1.1 PCA analysis

To investigate the possible differences in three types of turkey breast meat (normal, moderate and severe) at three ranges, *i.e.* VIS (550-700 nm), NIR (700-1100 nm) and VIS-NIR (550-1100) wavelengths, a PCA model was carried out.

4.4.1.2 Prediction model and spectra pre-processing

Different pre-processing of the raw spectra was performed before building the calibration models using PLS, for example (SNV, MSC, 1^{st} D, baseline correction, 2^{nd} D and smoothing) and combination from them. Visible and near-infrared spectra with eleven quality traits *e.g.* color indexes (a*, b* and L*), physical parameters (pH, uptake for marinated, cooking loss and drip loss) in addition to proximate chemical (moisture content, crude fat, protein content and ash), for the three types of turkey breast meat (normal, moderate and severe) were used to build PLS models.

Full cross-validation (each sample temporarily excluded from model development but still ultimately involved in the development of the model) was used as the validation method during building PLS models, in which one validation sample was removed from the calibration set and the PLS model

was then established based on the remaining calibration samples (ElMasry *et al.*, 2011). The calibration was made based on the averages of three spectra for each breast meat type. After that, this calibration was applied to predict chemical quality traits to investigate whether it was possible to discriminate normal turkey breast fillets from WS fillets (moderate and severe) based on these values. Then the quality traits of samples from the independent prediction set were used to confirm the predictive ability of the established PLS model.

4.4.1.3 Model performance

To know the predictive ability of the chosen PLS model different statistical measurements were used as the following:

1. Root-mean-square error (RMSE) estimated by calibration and prediction ($RMSE_{cal}$ and $RMSE_p$), these calculate the accuracy of calibration and prediction as the below formulas:

$$RMSE_{cal} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n-2}} \qquad (4.9)$$

$$RMSE_P = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \qquad (4.10)$$

Where:

- $\hat{y}_i$ and y_i are the predicted and observed values of sample i,
- n: number of samples.

2. The coefficient of determination in calibration (R^2_c) and prediction (R^2_p), these values describe how well the obtained data points fit the line of PLS regression model. These values range from 0 to 1.

Commonly, the model, which has the highest coefficients of determination (R^2_{cal} and R^2_p) and lowest root-mean-square error ($RMSE_{cal}$, $RMSE_p$) as well as a small difference between $RMSE_{cal}$ and $RMSE_p$, is adopted as an acceptable model (He *et al.,* 2013).

3. The ratio of performance deviation (RPD), this is equal to the standard deviation (SD) of the chemical values divided to RMSE.

$$RPD = \frac{SD}{RMSE} \qquad (4.11)$$

In general, different studies suggest that PLS model with an RPD value less than 2.5 doesn't provide a sufficient prediction, while RPD value between 2 and 3 considered as a good PLS model, whereas model with RPD value more than 3 gives an excellent prediction (Nicolai *et al.,* 2007).

4. Range error ratio (RER), this is equal to the range in the compositional values (*i.e.* the maximum value minus the minimum value) divided by the RMSE.

$$RER = \frac{Max - Min}{RMSE} \qquad (4.12)$$

American Association of Cereal Chemists (AACC) Method 39- 00.01 put threshold to accept the PLS according to RER value (AACC, 1999). Any model with RER value more than four is qualified for further screening calibration. While RER value is more than or equal to 10, the model is acceptable for quality control. Finally, the model considered very well for research quantification when its value equal to or more than 15 (Rambo *et al.*, 2013; Nduwamungu *et al.*, 2009).

5. Relative error (RE), it is defined as the absolute error relative to the size of all measurement, calculated as the next formula:

$$RE = \frac{RMSE}{(\frac{Max + Min}{2})} \qquad (4.13)$$

The R^2, RPD, RER in addition to RE values don't have a unit (dimensionless), that means they can be compared on the same basis between PLS models for different parameters (Kapper *et al.*, 2012).

Although the numbers of samples are few, the objective of the study is to test the potential of VIS-NIR technique to predict chemical changes between WS and normal turkey breast fillets.

4.4.2 Statistical analysis

Statistical analysis was applied to identify differences in quality traits between normal and WS (moderate and severe) turkey fillets. The differences in quality traits were evaluated by ANOVA. The model tested the major effects of WS degrees (normal, moderate or severe) and replication, in addition to the interaction term using the general linear model (GLM) (SAS, 1988) on meat quality traits. Comparisons of means were performed by the Tukey's honestly significant difference multiple range tests at a 5% significance level.

5. Results and Discussion

5.1 Chemical characteristics

Descriptive statistics including mean, range, maximum and minimum values, standard deviations (SD) and coefficients of variation (CV) obtained from quality parameters (*i.e.* color indexes (a*, b* and L*), pH, drip loss, cooking loss and marinade uptake) in addition to chemical quality traits (*i.e.* crude fat content, protein content, ash content and moisture content) of turkey breast meat used for the calibration and validation sets are shown in Table 1.

In general, there were many changes in the physio-chemical quality traits due to the presence of white striping defects in the turkey breast meat. The values color indexes obtained in this study were in agreement with previous studies (Petracci *et al.*, 2014; Sihvo, Immonen, & Puolanne, 2014; Mudalal *et al.*, 2015). It was found that the obtained range of L* value for all groups was 56.93– 71.53. Therefore, fillets in all groups were classified as PSE (L*>53). Color indexes L*, a* and b* had wide ranges (63.69-71.53, 0.1-4.49 and 1.57-6.99), respectively for normal meat. In addition, redness index (a*) of normal meat had CV higher than moderate and severe white striped meat, *i.e.* 76.28 vs. 54.36 and 49.67, respectively.

On the contrary, lightness (L*) and yellowness indexes (b*) of normal meat exhibited lower CV than moderate and severe white striped meat. Moderate and severe white striped meat exhibited significantly higher values of redness index (a*), *i.e.* 2.98 and 3.06 vs. 1.56, at $p<0.05$ and lower values of yellowness index (b*), *i.e.* 7.27 and 7.98 vs. 4.20, at $p<0.05$, if compared with normal meat, respectively. Moderate and severe white striped fillets exhibited higher a*-values (*i.e.* 2.98 and 3.06 vs. 1.56, at $p<0.05$) than normal fillets. Similar results have been observed in previous studies (Mudalal *et al.*, 2014; Sihvo *et al.*, 2014). This result may be explained due to the significant increase in the pH of white striped fillets.

In the same context, moderate and severe white striping fillets had significantly b*-values (7.27 and 7.98 vs. 4.29, at $p<0.05$) higher than normal fillets. The increase in b*-values may be attributed to increasing in fat content that has been observed in this study which also was consistent with previous studies (Kuttappan *et al.*, 2012; Petracci *et al.*, 2014).

pH ranged from 5.93 to 6.24, 5.92 to 6.25, and 6.12 to 6.30 for normal, moderate and severe white striped meat, respectively. Severe white striping meat had significantly pH higher than normal and moderate meat.

These results were in agreement with previous studies (Mudalal *et al.*, 2015; Tijare *et al.*, 2016).

Marinade uptake ranged from 9.38 to 17.07, 9.21 to 21.42 and 13.48 to 24.61 for severe, moderate, and normal meat, respectively, but there were no significant differences between groups.

The presence of white striping did not exhibit any effect on drip loss, cooking, moisture and ash. It was that moderate and severe white striped meat had higher fat contents 1.27 and 2.17 vs. 1.02, at $p<0.05$ and lower protein contents 23.12 and 21.06 vs. 24.07, at $p<0.05$ when compared to normal meat. This may be attributed due to myodegeneration companied by fibrosis and lipidosis (Kuttappan *et al.*, 2012; Petracci *et al.*, 2014).

Table 1: Approximate chemical composition, color indexes and pH in normal turkey breast muscle and white striping (moderate and severe).

	Levels of white striping[1]															
	Normal					Moderate					Severe					
Properties	Mean± SD	Max	Min	Range	CV	Mean	Max	Min	Range	CV	Mean	Max	Min	Range	CV	P
Color indexes a*	1.56^{c}±1.19	4.49	0.1	4.39	76.28	2.98^{b}±1.62	5.55	0.99	4.56	54.36	3.06^{a}±1.52	4.75	1.01	3.74	49.67	<0.05
b*	4.20^{c}±1.70	6.99	1.57	5.42	40.48	7.27^{b}±2.67	11.84	3.62	8.22	36.73	7.98^{a}±1.96	10.04	3.94	6.10	24.56	<0.05
L*	66.59±2.50	71.53	63.69	7.84	3.75	63.53±4.17	70.13	56.93	13.20	6.56	64.31±4.18	69.62	57.72	11.90	6.50	0.12
pH	6.10 ^{a}±0.10	6.24	5.93	0.31	1.64	6.13 ^{a}±0.09	6.25	5.92	0.33	1.47	6.19 ^{b}±0.06	6.30	6.12	0.18	0.97	<0.05
Marinade uptake%	15.93±3.63	24.61	13.48	11.13	22.79	15.96±3.75	21.42	9.21	12.21	23.50	13.72±2.51	17.07	9.38	7.69	18.29	0.23
Drip loss (%)	6.98±1.23	8.54	3.51	5.03	17.62	6.16±1.15	12.33	3.51	8.82	93.34	6.38±1.15	8.56	4.48	4.08	18.03	0.53
Cooking loss (%)	18.59±1.81	22.01	15.15	6.86	9.74	18.00±1.79	21.41	14.77	6.64	9.94	18.28±2.57	23.94	15.81	8.13	14.06	0.78
Moisture content%	75.48±1.15	77.05	73.4	3.65	1.52	76.09±1.55	79.66	74.15	5.51	2.04	75.52±1.19	77.73	73.56	4.17	1.58	0.53
Fat%	1.02^{c}±0.91	3.10	0.33	2.77	89.22	1.27^{b}±1.05	4.15	0.55	3.60	82.68	2.17^{a}±1.10	4.74	1.38	3.36	50.69	<0.05
Protein%	24.07^{a}±2.67	27.18	15.75	11.43	11.09	23.12^{b}±1.48	25.56	21.53	4.03	6.40	21.06^{c}±1.58	24.31	19.06	5.25	7.50	<0.05
Ash%	2.01±1.12	4.92	1.39	3.53	55.72	1.73±0.42	2.61	1.32	1.29	24.28	1.56±0.24	2.07	1.29	0.78	15.38	0.36

[1] The occurrence of white striping was classified into normal, moderate and severe according to Kuttappan *et al.* (2012).

[a-c] Means within a row followed by different superscript letters differ significantly (P< 0.05).

5.2 Spectral characterization

Typical mean spectral curves representing the three levels of white striping fillets in the wavelength range 550–1100 nm are shown in Figure 13. The depressions and peaks in spectra showed the strong and weak absorbance characteristics of the samples, within the range of study. The spectra of normal, moderate (WS) and severe (WS) breast fillets showed similar absorption bands which were in agreements with previous studies (Cozzolino *et al.*, 1996; Fumiere *et al.*, 2000).

NIR spectra often contain undesired scattering variation due to heterogeneous content and sample surface amongst others. The scattering effect in NIR consists of a multiplicative effect and an additive effect. The additive effect is reflected as a baseline offset. The multiplicative effect is reflected as a slope that scales the entire spectrum. Data pre-treatment is needed to minimize these complex baseline variations and scattering effects. NIR spectra of the samples set were pre-processed using SNV to delete slope variation and to correct for scattering effects as represented in Figure 14.

Light scattering in fresh meat samples doesn’t always travel the same distance before it is detected. As a longer light traveling path corresponds to a lower relative reflectance value while more light is absorbed. This causes a parallel

translation of the spectra. For that reason, multiplicative scatter correction (MSC) was used to eliminate these effects (Li & He, 2006) as shown in Figure 15. Savitzky–Golay first derivatives (1^{st} D) was done to delete baseline flung in meat spectral data and small spectral differences were strengthened, this followed by Savitzky–Golay smoothing (SG) to prevent increasing the noise which came from the derivative as found in Figure 16. The relative values in another region of spectra, however, varied from sample to sample, which might be due to changes in surface texture and moisture content of three types of fillets.

Six bands (peaks at 550, 574, 580, 600, 630 and 643 nm) in visible region (550-700 nm) and eight bands in the NIR region have been observed (Figure 17). Several researchers found similar bands and spectral features (Barlocco *et al.*, 2006; Andrés *et al.*, 2008; De Marchi *et al.*, 2012). Absorption bands at 550 to 580 nm were associated to the Soret band attributed to the traces of erythrocytes of myoglobin with both haemoglobin and oxyhaemoglobin absorption (Stryer & Latchman, 1995) as well as to oxymyoglobin (Liu & Chen, 2000). Our findings showed that severe white striping fillets had higher absorption at 550, 574 and 580 nm than normal fillets. This result may be attributed due to discoloration over the surface of white striped fillets.

Water absorbs strongly in the NIR region and naturally shows a wide band as a result of hydrogen bonding interactions between it and other components in turkey meat (Ellekjaer & Isaksson, 1992). The mean spectrum in the NIR region has absorption bands at 980 nm and it could be related to the second overtone of the OH- vibrational mode of water (Bowker *et al.*, 2014).

The absorption at 760 and 908 nm corresponds to the deoxhaemoglobin (Hollo *et al.*, 1986) and the third overtones of C-H bonds (Weyer & Workman Jr, 2007), respectively. The identified band at 552 nm related to myoglobin (Cozzolino *et al.*, 1996). The absorption band at 574 nm was associated with oxyhemoglobin (Mitsumoto *et al.*, 1991). Absorption bands at 540 and 580 nm were associated with both myoglobin and oxymyoglobin, respectively (Cozzolino & Murray, 2004).

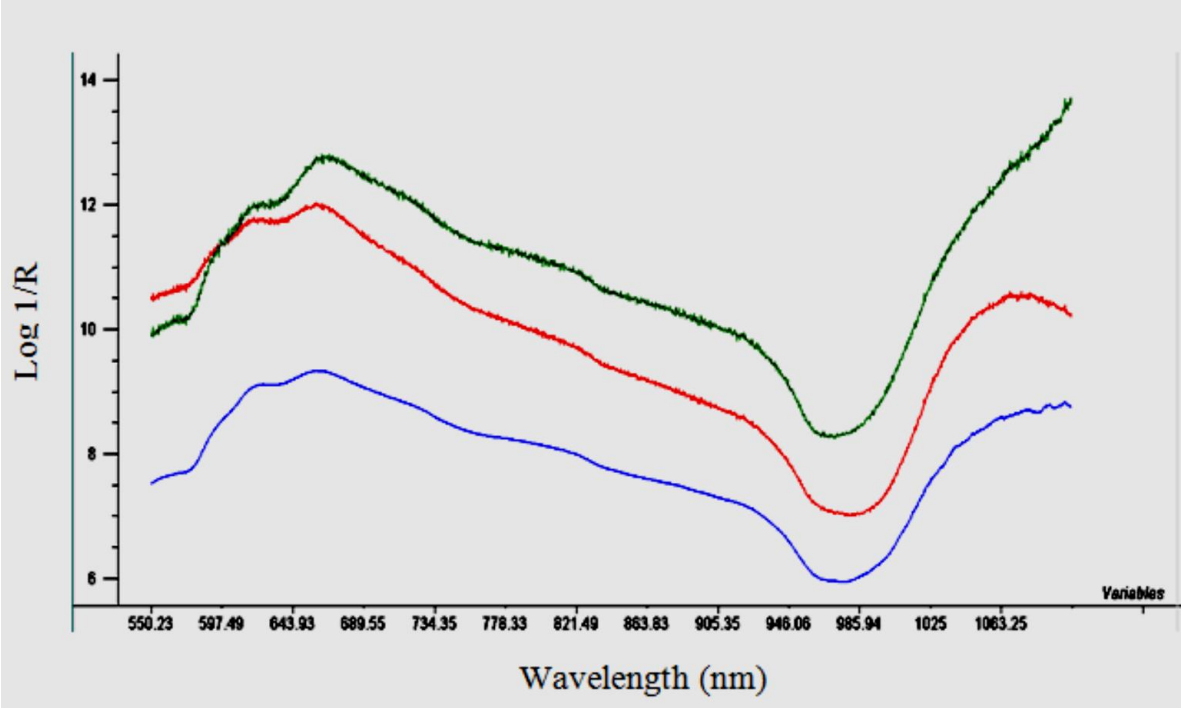

Figure 13. A typical VIS-NIR (550-1100 nm) spectral curves obtained from turkey fillets. Normal fillets (red), moderate WS fillets (blue), and sever WS (green) fillets, without pre-processing.

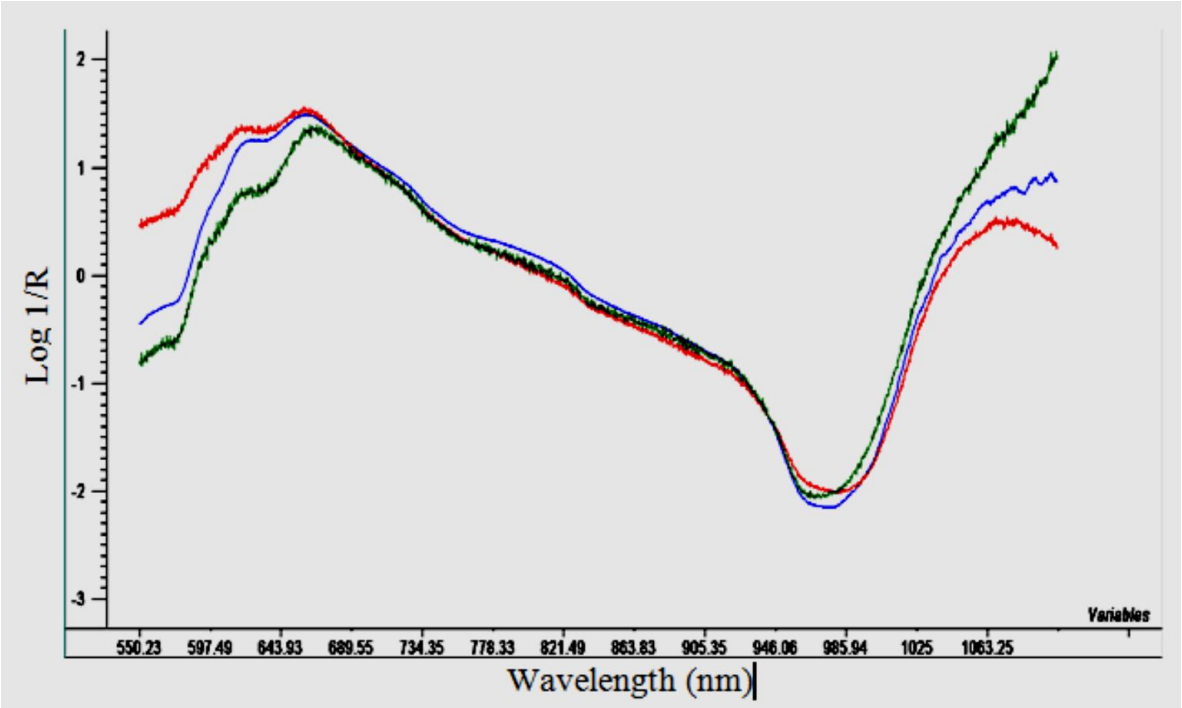

Figure 14. The effect of SNV preprocessing on the spectra obtained from turkey fillets. Normal fillets (red), moderate WS fillets (blue), and sever WS (green) fillets.

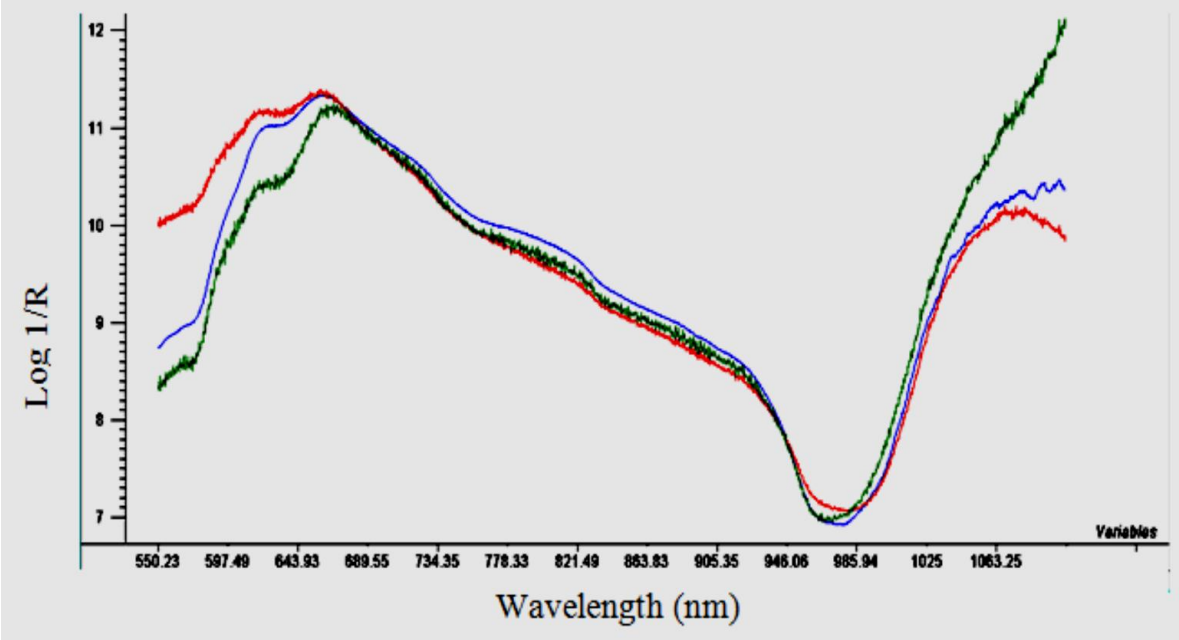

Figure 15. The effect of MSC preprocessing on the spectra that obtained from turkey fillets. Normal fillets (red), moderate WS fillets (blue), and sever WS (green) fillets.

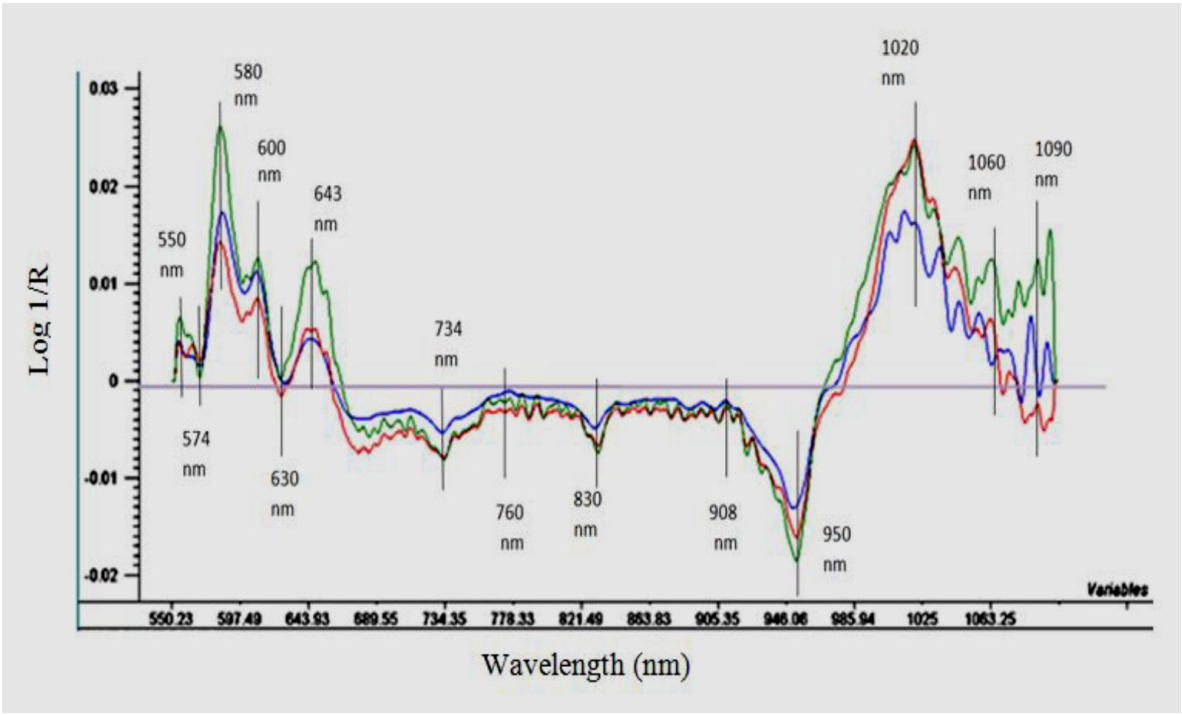

Figure 16. The effect of the first derivative and smoothing preprocessing on the spectra obtained from turkey fillets with different absorption bands. Normal fillets (red), moderate WS fillets (blue), and sever WS (green) fillets.

5.3 PCA

Principle component analysis has been carried for VIS-NIR regions spectrum considering the three levels of muscle abnormalities (normal, moderate and severe). PCA showed an ability to distinguish the three groups (normal, moderate WS, and severe WS) from each other as shown in Figures17- 19.

In this analysis, 2PCs for VIS, NIR and VIS-NIR region explained 99%, 100% and 98% of the variance, respectively. Our finding showed that PCA had high performance in separating normal turkey breast meat from abnormal meat (moderate and severe). These results were in agreement with previous studies where VIS-NIR spectroscopy with PCA was used to separate poultry and meat product to different categories (Wold *et al.,* 2017).

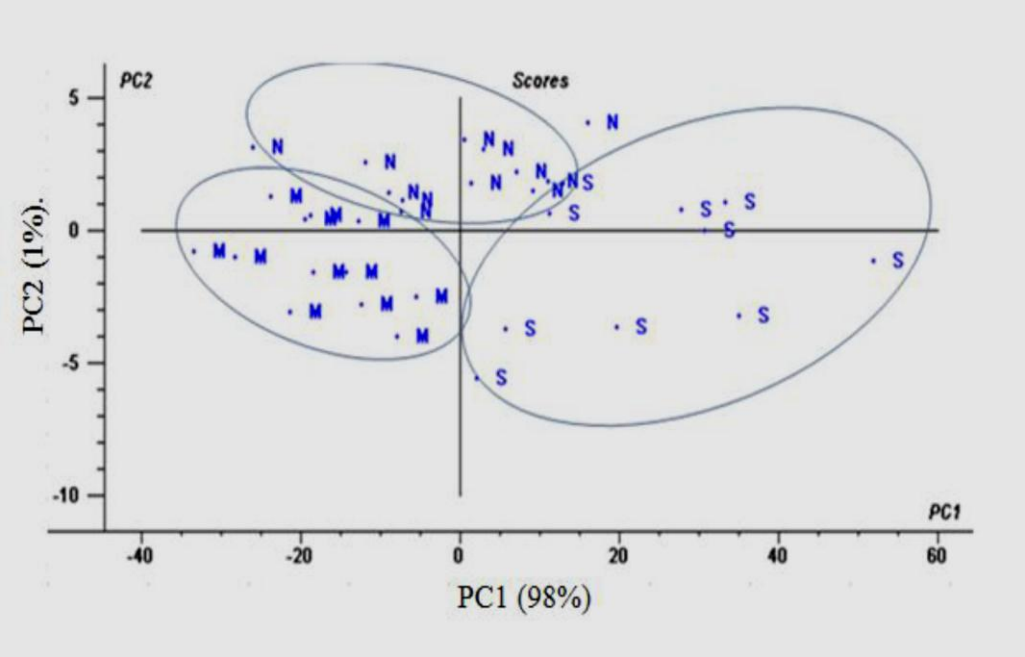

Figure 17. Score plot of PCA model based on VIS (550- 700 nm) spectra of turkey fillets. Normal fillets (N), moderate WS fillets (M) and sever WS (S) fillets. Two PCs explained 99% of the data variation.

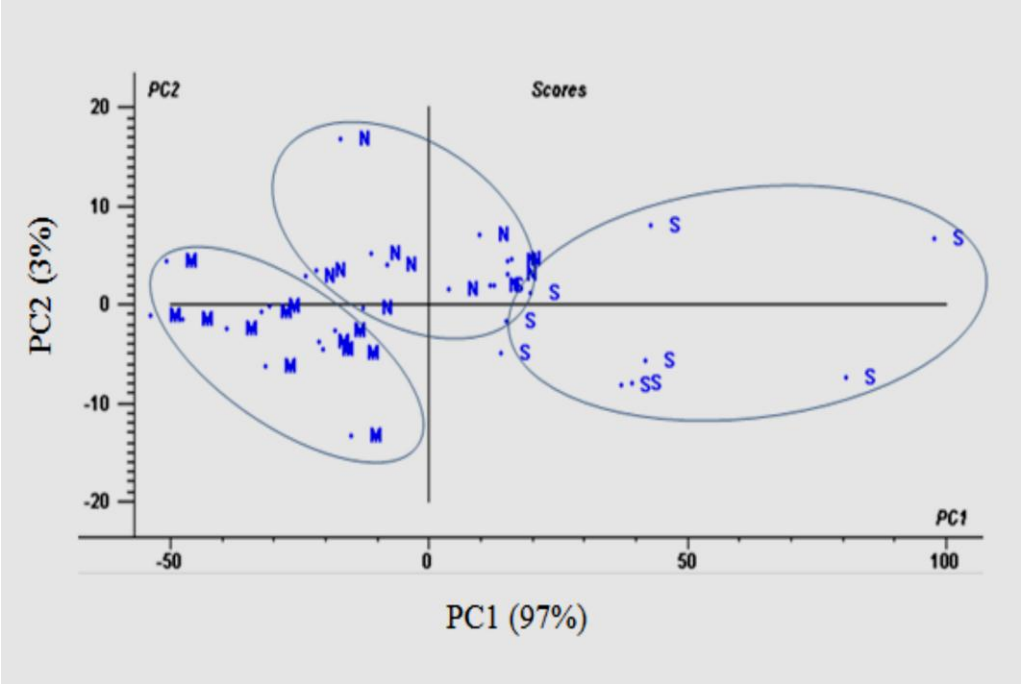

Figure 18. Score plot of PCA model based on NIR (700-1100 nm) spectra of turkey fillets. Normal fillets (N), moderate WS fillets (M) and sever WS (S) fillets. Two PCs explained 100% of the data variation.

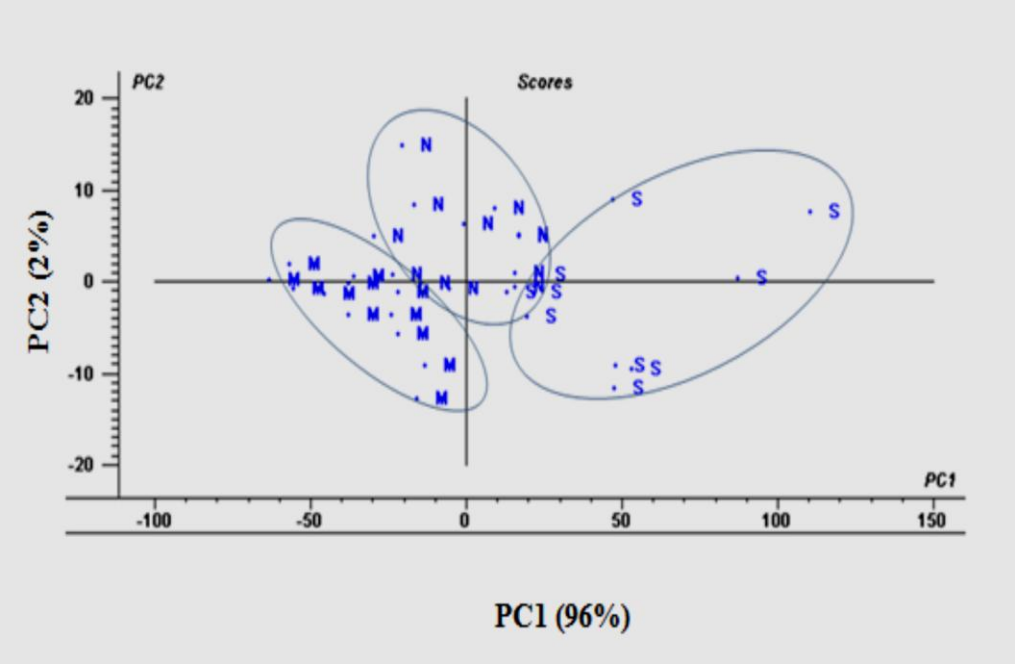

Figure 19. Score plot of PCA model based on VIS-NIR (550-1100 nm) spectra of turkey fillets. Normal fillets (N), moderate WS fillets (M) and sever WS (S) fillets. Two PCs explained 98% of the data variation.

5.4 PLS

Prediction of chemical composition for three groups of meat samples was performed based on different pre-treated spectral for different quality traits, but the same regression model was applied to each group separately. The quality parameters were evaluated from visible and near spectra by PLS analysis. The error of prediction and correlation coefficients of models showed the potential application of VIS-NIR spectra to differentiate meat quality parameters between normal and white striping (moderate and severe) turkey breast meat.

The results of color indexes (a*, b* and L*) obtained from calibration and full cross-validation PLS regression model for normal, moderate, and severe white striping turkey breast meat samples are shown in Table 2. The prediction values of coefficient of determination (R^2_p) were 0.91 and 0.57, the ratio of performance deviation (RPD) were 3.21 and 1.26, and range error ratio (RER) were 11.86 and 3.11 for the redness index (a*) of normal and severe groups, respectively. Our finding showed that VIS-NIR spectroscopy was satisfactory to differentiate normal from severe WS turkey fillets by using redness index (a*). Whereas the prediction ability was also high for a* value for moderate WS; R^2_p was 0.89, RPD was 2.74 and RER was 7.72, so it is unable to

distinguish between normal and moderate WS. Figures 20- 22 show the scatter plots of a* PLS developing model.

Table 2: Statistics of the calibration equations for color indexes (a*, b* and L*) of the three types of turkey breast meat of the best fit and validation.

			Statistical parameters for calibration and prediction									
	Level of white striping	Preprocessing	R^2_{cal}	$RMSE_{cal}$	RPD_{cal}	RE_{cal}	RER_{cal}	R^2_p	$RMSE_p$	RPD_p	RE_p	RER_p
Redness index (a*)	Normal	SNV+1StD	0.93	0.30	3.97	0.13	14.63	0.91	0.37	3.22	0.16	11.86
	Moderate		0.98	0.22	7.34	0.07	20.73	0.89	0.59	2.74	0.18	7.73
	Severe		0.81	0.68	2.23	0.24	5.50	0.57	1.20	1.27	0.42	3.12
Yellowness index (b*)	Normal	SNV+1StD	0.98	0.20	8.50	0.05	27.10	0.95	0.46	3.69	0.11	11.78
	Moderate		0.32	1.88	1.42	0.24	4.37	0.14	2.35	1.14	0.30	3.50
	Severe		0.95	0.40	4.90	0.06	15.25	-3.06	4.16	0.47	0.60	1.47
Lightness index (L*)	Normal	MSC+ SNV	0.99	0.20	12.50	0.01	39.20	0.94	0.58	4.31	0.01	13.52
	Moderate		0.99	0.25	16.68	0.01	52.80	0.87	1.67	2.48	0.03	7.90
	Severe		0.98	0.44	9.50	0.01	27.04	0.81	2.03	2.06	0.03	5.86

Root-mean-square error estimated by calibration ($RMSE_{cal}$), the coefficient of determination in calibration (R^2_c), root-mean-square error estimated by prediction ($RMSE_p$), the coefficient of determination in prediction (R^2_p), the ratio of performance deviation (RPD), relative error (RE) and range error ratio (RER).

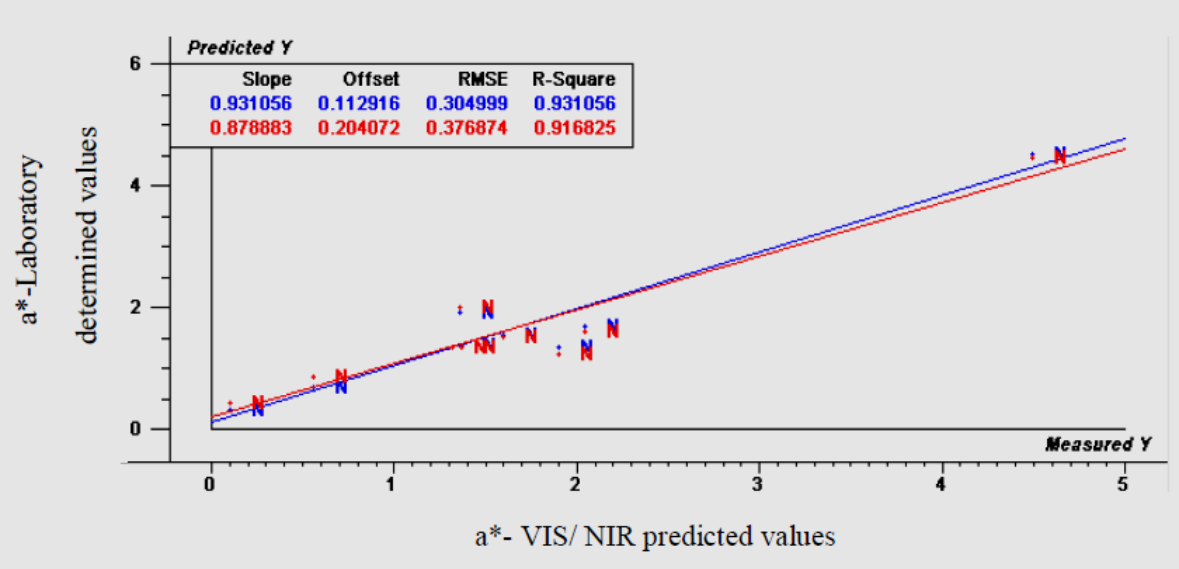

Figure 20. The relationship between laboratory determined and VIS-NIR predicted values for a* normal turkey breast meat using PLS and full cross validation for 10 samples (blue line for calibration set and red line for validation set).

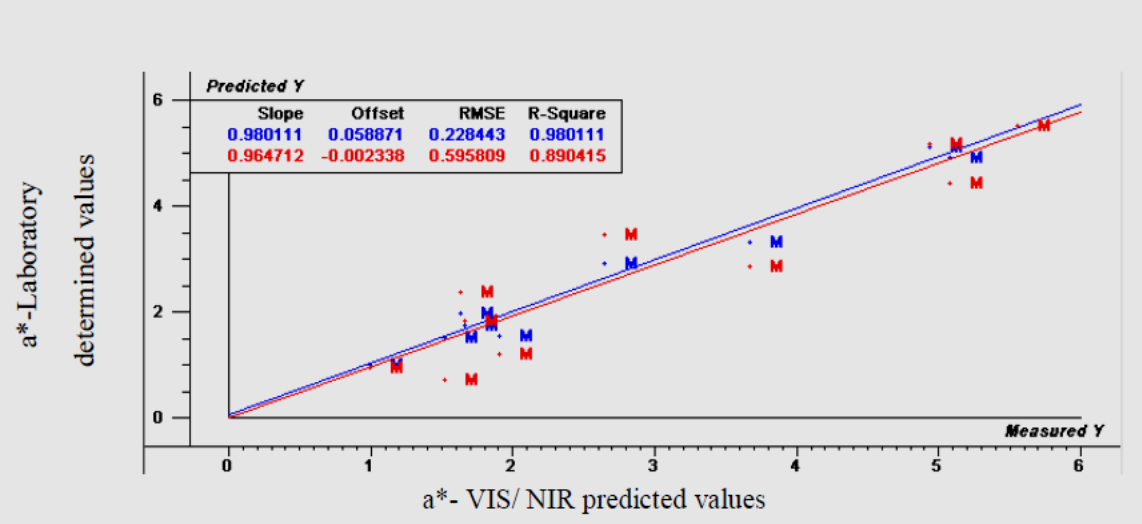

Figure 21. The relationship between laboratory determined and VIS-NIR predicted values for a* moderate WS turkey breast meat using PLS for and full cross validation for 9 samples (blue line for calibration set and red line for validation set).

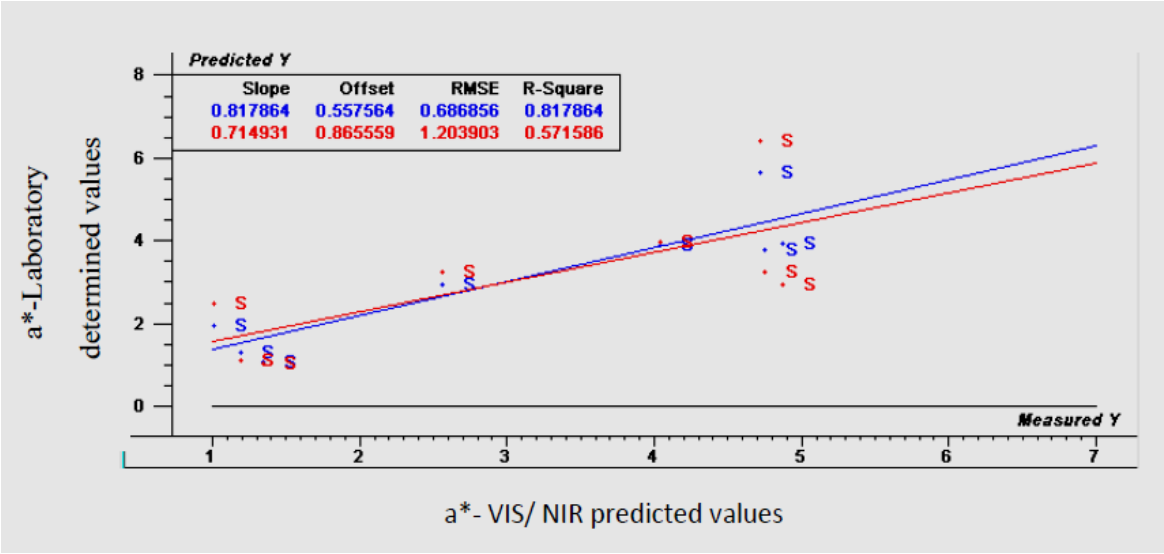

Figure 22. The relationship between laboratory determined and VIS-NIR predicted values for a* severe WS turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

The predictive ability for VIS-NIR was satisfactory to differentiate normal from defected turkey fillets according to yellowness index (b*). As represented in Figures 23-25, R^2_p were 0.95, 0.14 and -3.06 for normal, moderate and severe fillets, respectively. RPD was 3.69 for normal, 1.13 for moderate WS, and 0.47 for severe WS and RER was 11.78, 3.49 and 1.46 for normal, moderate and severe WS.

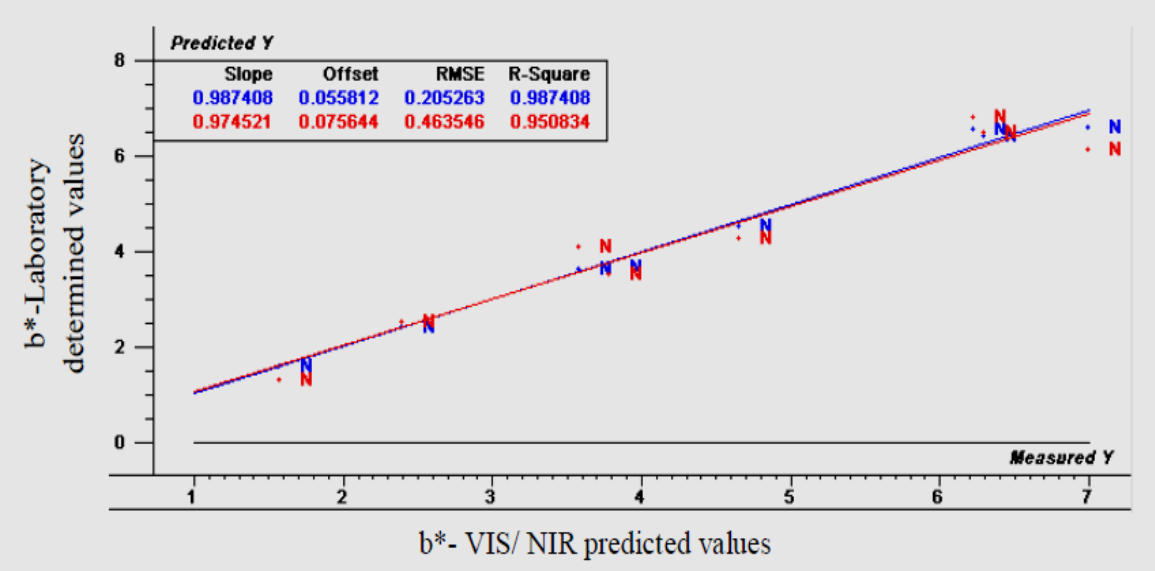

Figure 23. The relationship between laboratory determined and VIS-NIR predicted values for b* normal turkey breast meat using PLS and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

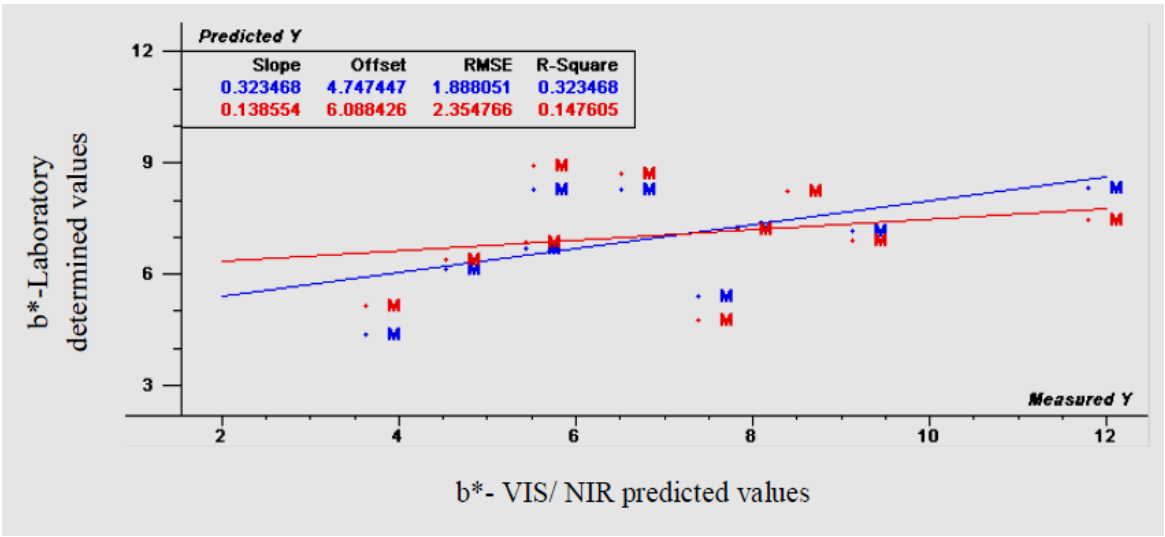

Figure 24. The relationship between laboratory determined and VIS-NIR predicted values for b* moderat WS turkey breast meat using PLS and full cross validation for 10 samples (blue line for calibration set and red line for validation set).

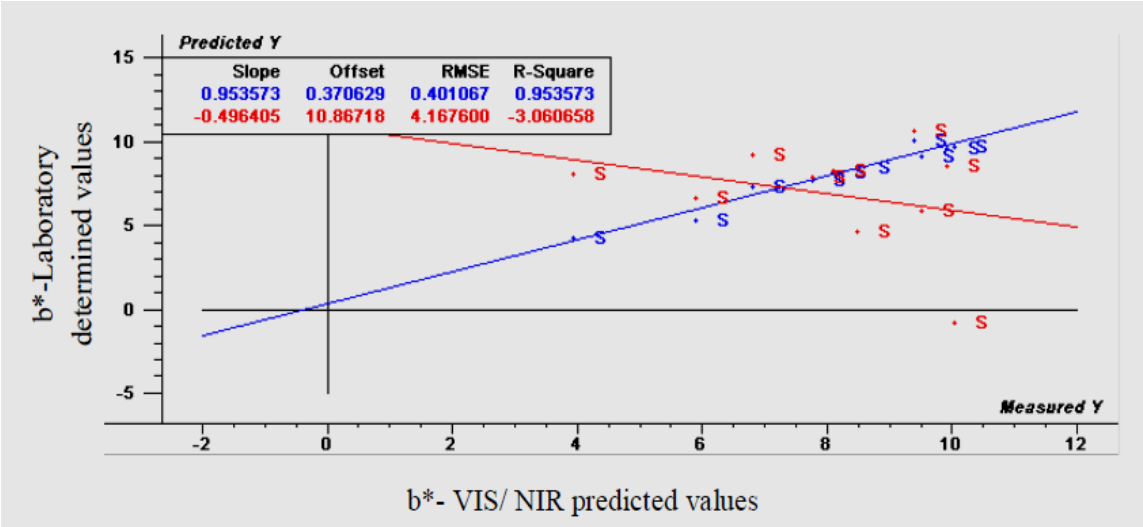

Figure 25. The relationship between laboratory determined and VIS-NIR predicted values for b* sever WS turkey breast meat using PLS and full cross validation for 10 samples (blue line for calibration set and red line for validation set).

It was found that L* value had R^2_p of 0.94, 0.87 and 0.81, RPD were 4.31, 2.49 and 2.05, and RER were 13.51, 7.90 and 5.86 for normal, moderate and severe white striping fillets, respectively. Figures 26, 27 and 28 show the scatter plots of developing model according to L*.

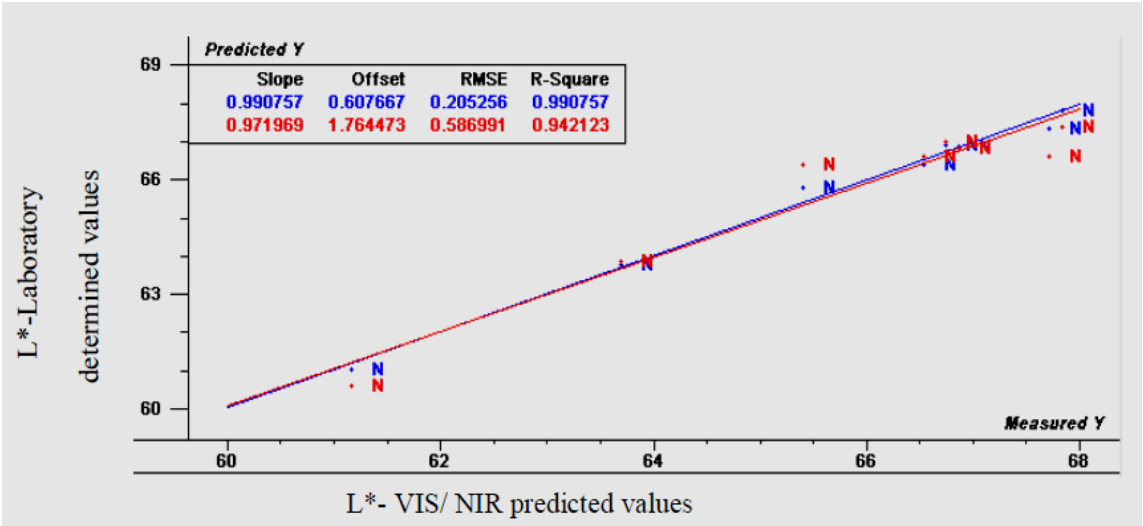

Figure 26. The relationship between laboratory determined and VIS-NIR predicted values for L* of normal turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

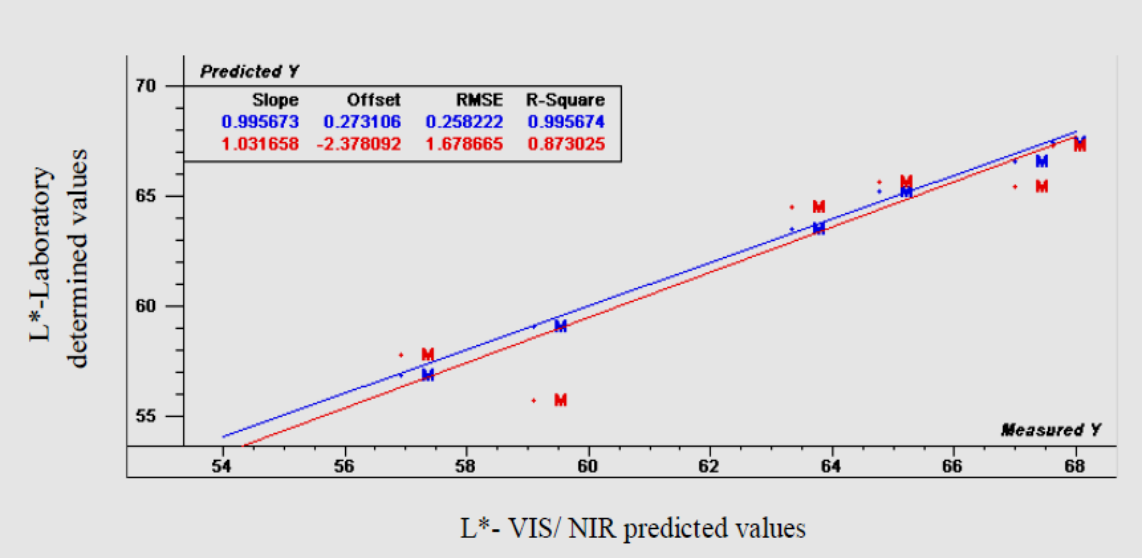

Figure 27. The relationship between laboratory determined and VIS-NIR predicted values for L* of moderate WS turkey breast meat using PLS for and full cross validation for 6 samples (blue line for calibration set and red line for validation set).

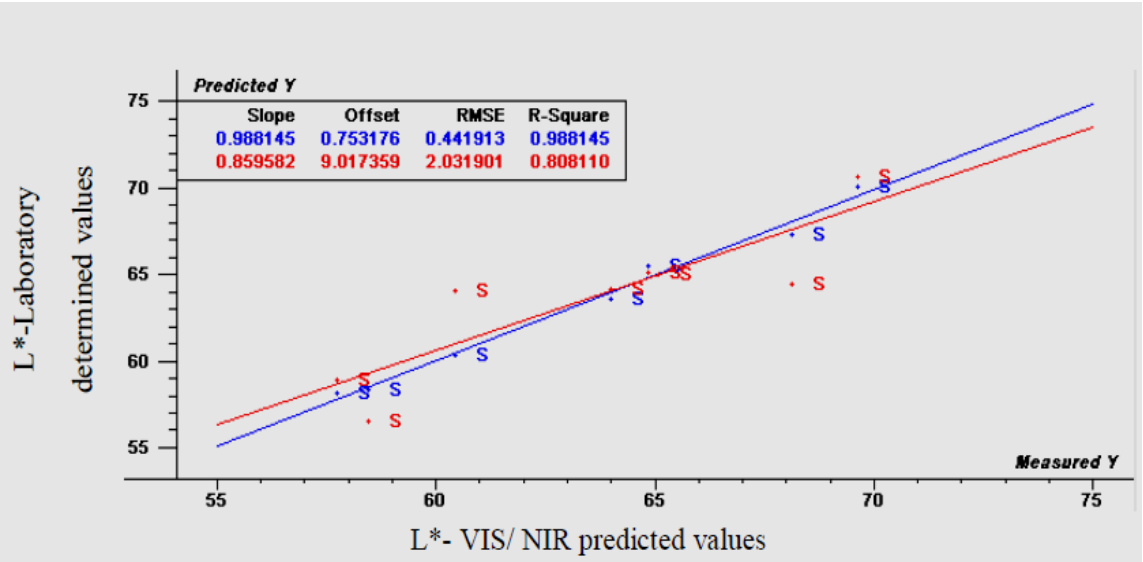

Figure 28. The relationship between laboratory determined and VIS-NIR predicted values for L* of normal turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

The results of the PLS model of (pH, marinade uptake, cooking loss and drip loss) quality traits for three turkey fillets types are presented in Table 3. The best fit of prediction values from the same regression model for pH is as the following: R^2_p were 0.95, 0.12 and 0.07, RPD were 5.00, -0.13 and -0.33, then RER was 15.00, -0.48 and 1.00 for normal, moderate WS and severe WS, respectively. According to PLS regression model for pH calibration, which is represented in Figures 29-31, VIS-NIR spectroscopy has the ability to differentiate between normal fillets from abnormal WS breast meat.

Table 3: Statistics of the calibration equations for quality traits of the three types of turkey breast meat of the best fit and validation, including $RMSE_{cal}$, R^2_c, $RMSE_p$, R^2_p, RPD, RE and RER.

			Statistical parameters for calibration and prediction									
	Level of white striping	Preprocessing	R^2_{cal}	$RMSE_{cal}$	RPD_{cal}	RE_{cal}	RER_{cal}	R^2_p	$RMSE_p$	RPD_p	RE_p	RER_p
pH	Normal	MSC+ SNV	0.99	0.01	10.00	0.01	31.00	0.95	0.02	5.00	0.01	15.50
	Moderate		0.66	0.05	1.80	0.30	6.60	0.12	-0.68	-0.1324	-0.11	-0.4853
	Severe		0.89	0.02	3.00	0.01	9.00	0.07	-0.18	-0.3333	-0.03	-1.00
Marinade uptake	Normal	MSC+ 1^{St} D	0.98	0.35	10.37	0.02	14.37	0.91	1.01	3.59	0.05	11.02
	Moderate		0.94	1.22	3.07	0.08	10.01	0.73	3.18	1.18	0.21	3.84
	Severe		0.97	0.32	7.84	0.02	24.03	0.70	1.29	1.94	0.10	5.96
Drip loss	Normal	_____	0.99	0.03	41.00	0.01	167.67	0.83	0.30	4.10	0.05	16.77
	Moderate		0.99	0.13	44.23	0.02	67.84	0.14	1.70	3.38	0.21	7.18
	Severe		0.99	0.06	19.17	0.01	68.00	-0.12	1.02	1.12	0.16	7.54
Cooking loss	Normal	SNV	0.99	0.18	10.06	0.01	38.11	0.97	0.35	5.17	0.02	19.60
	Moderate		0.83	0.74	2.419	0.04	8.97	0.73	1.04	1.74	0.06	6.38
	Severe		0.90	0.18	14.28	0.01	45.17	0.59	1.03	2.49	0.05	7.89

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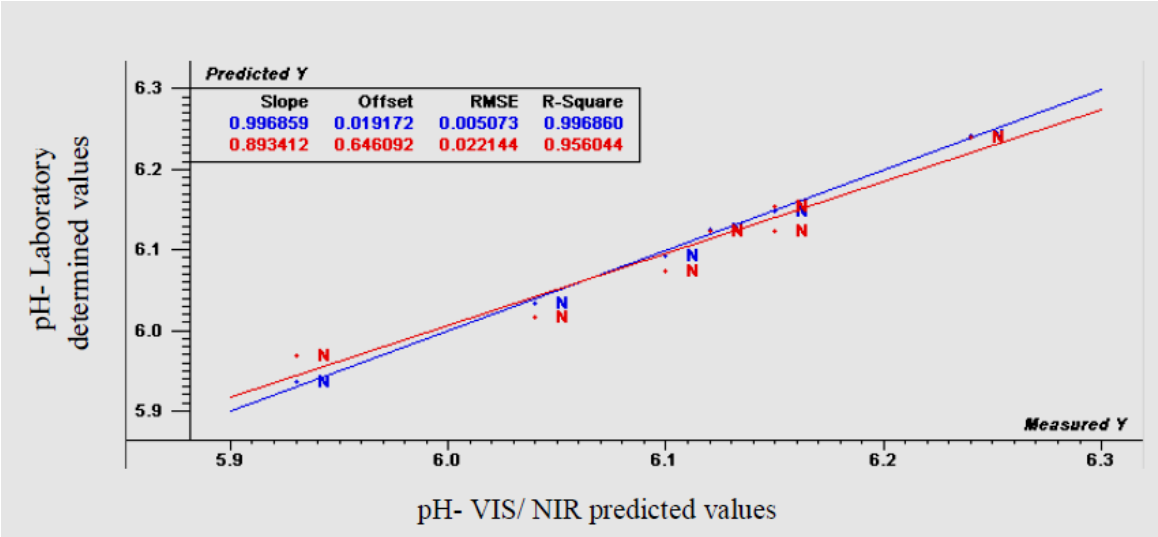

Figure 29. The relationship between laboratory determined and VIS-NIR predicted values for pH of normal turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

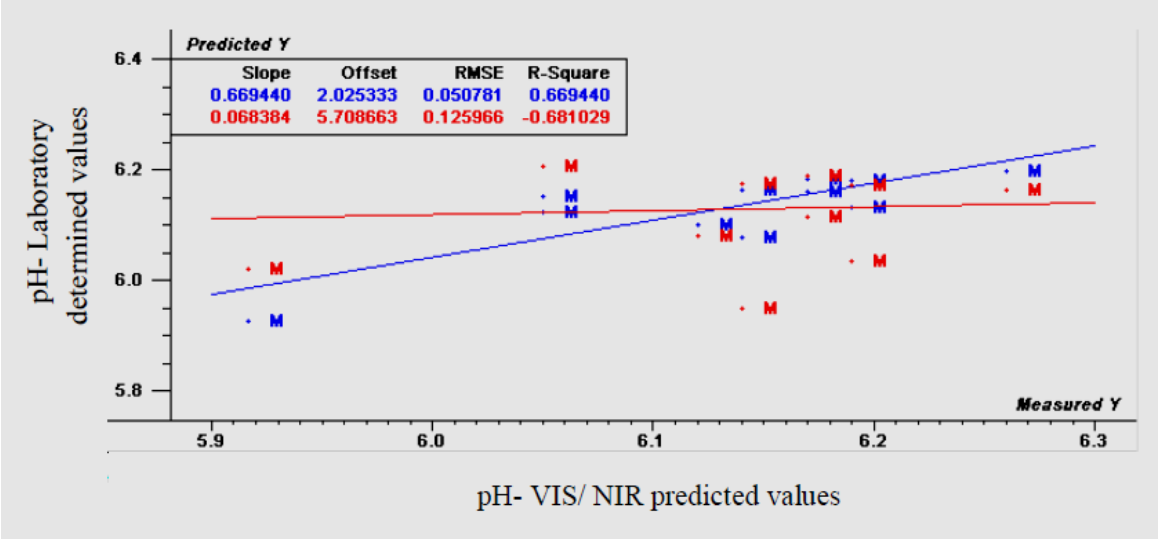

Figure 30. The relationship between laboratory determined and VIS-NIR predicted values for pH of moderat WS turkey breast meat using PLS for and full cross validation for 10 samples (blue line for calibration set and red line for validation set).

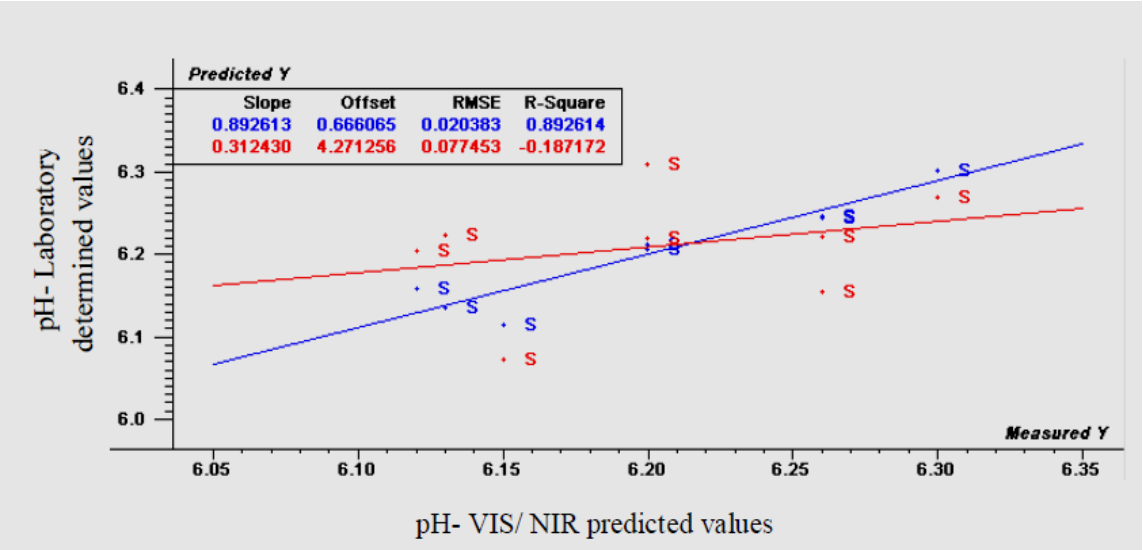

Figure 31. The relationship between laboratory determined and VIS-NIR predicted values for pH of sever WS turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

The prediction values for marinade uptake were as in the Figures 32-33. R^2_p were 0.91, 0.73 and 0.70, RPD were 3.59, 1.17 and 1.94, and moreover, RER were 11.01, 3.83 and 5.96 for normal, moderate and severe WS, respectively. Considering marinade uptake, VIS-NIR spectroscopy had the ability to detect normal fillets from abnormal.

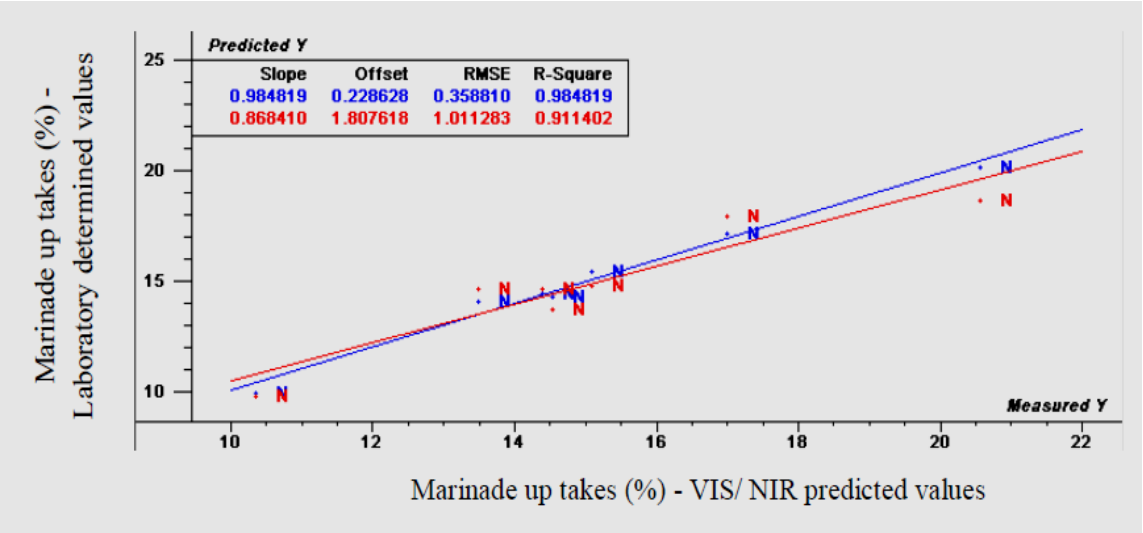

Figure 32. The relationship between laboratory determined and VIS-NIR predicted values for marinade up takes of normal turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

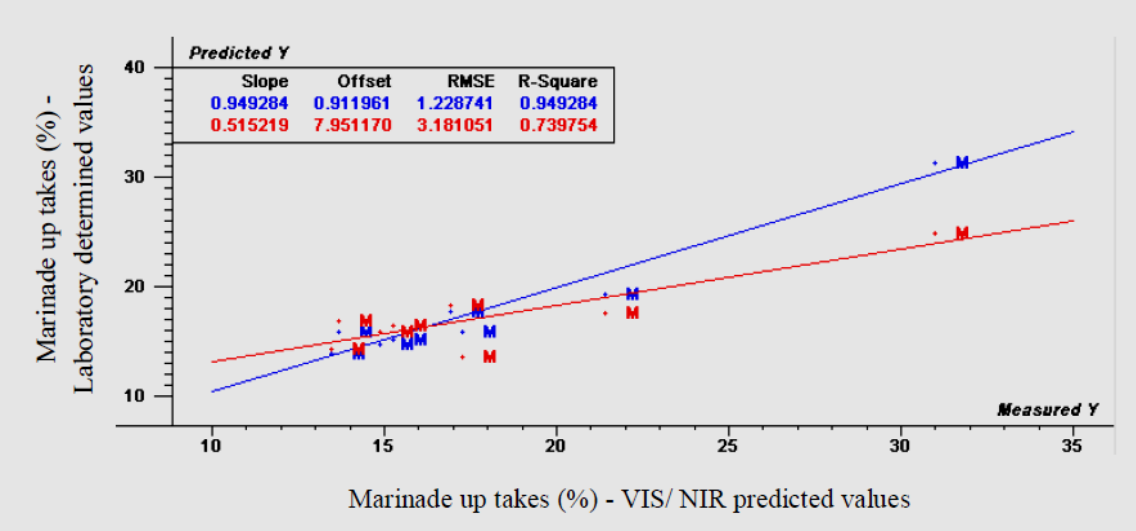

Figure 33. The relationship between laboratory determined and VIS-NIR predicted values for up- take for marinated of moderat WS turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

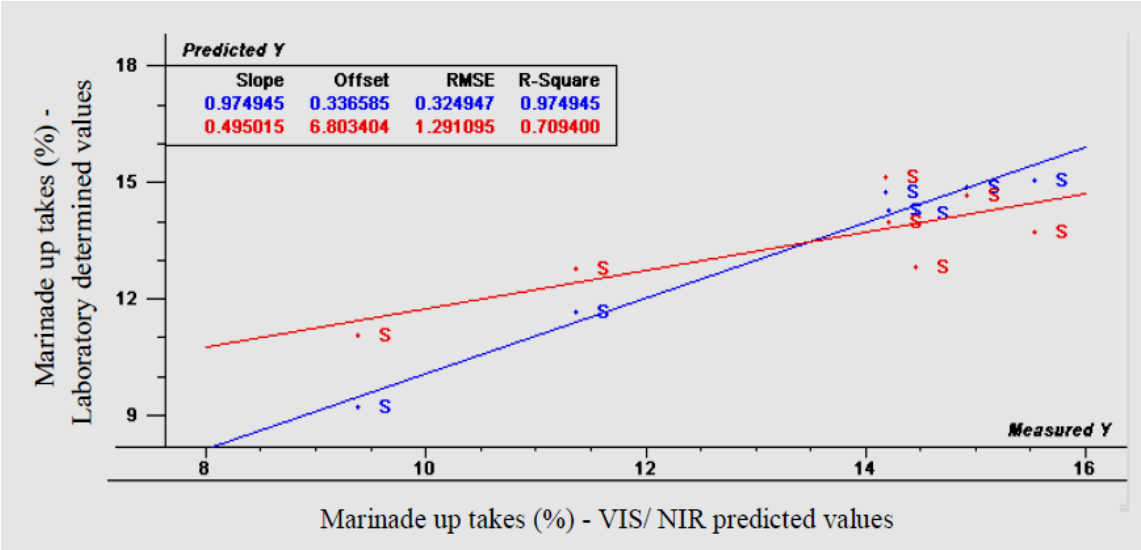

Figure 34. The relationship between laboratory determined and VIS-NIR predicted values for marinade up takes of severe WS turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

In addition to that, R^2_P values for drip loss were 0.81, 0.14 and -0.12, RPD were 4.1, 3.38 and 1.12, also RER were 16.76, 7.18 and 7.53 for normal, moderate and severe WS, respectively. According to the drip loss prediction results VIS-NIR has the ability to differentiate between normal and defect WS. The PLS plots for turkey breast samples according to this trait are shown in Figures 35-37.

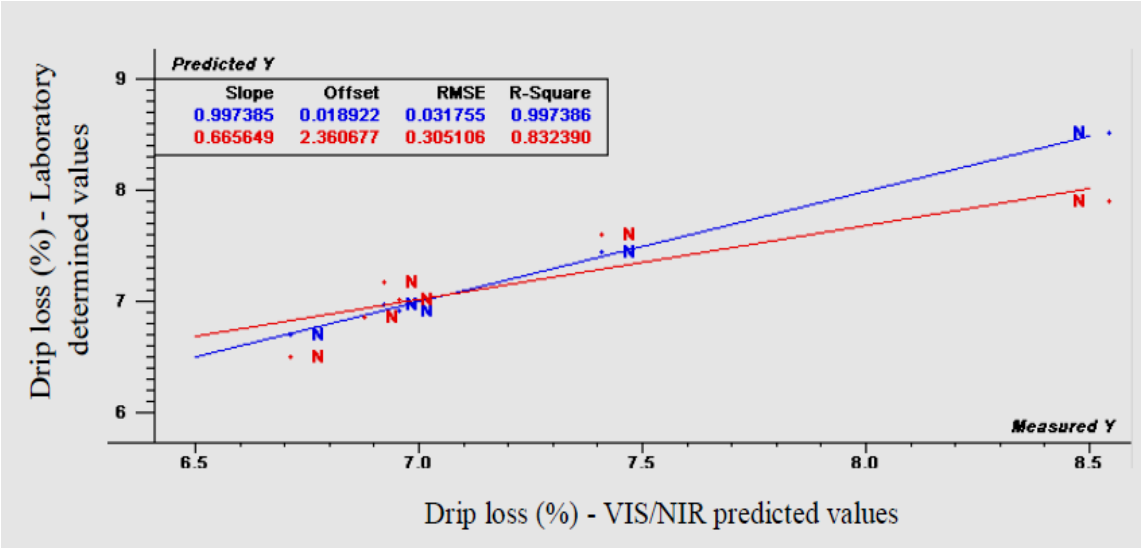

Figure 35. The relationship between laboratory determined and VIS-NIR predicted values for drip loss (%) of normal turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

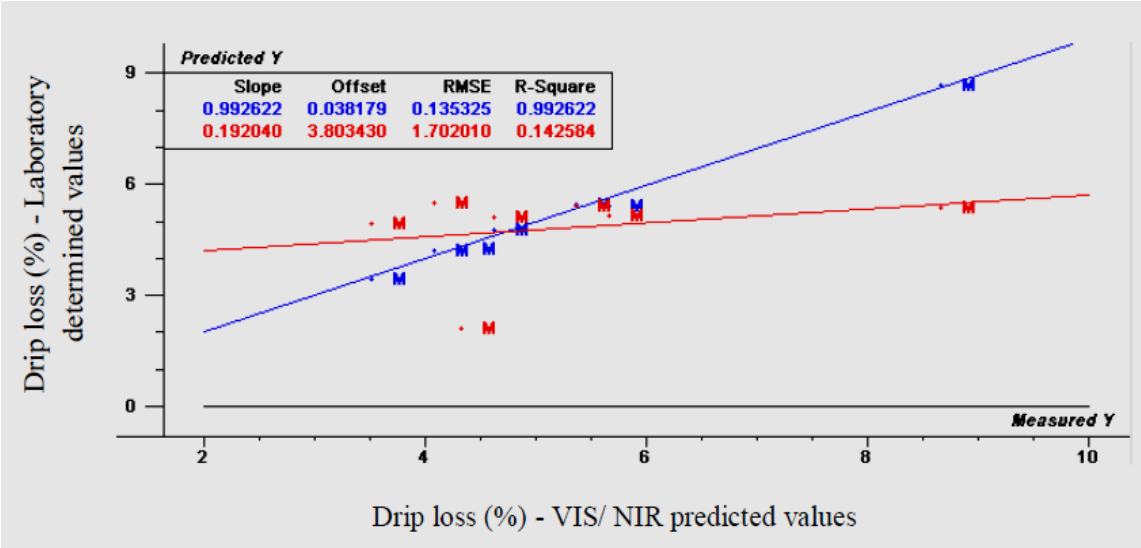

Figure 36. The relationship between laboratory determined and VIS-NIR predicted values for drip loss (%) of moderate WS turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

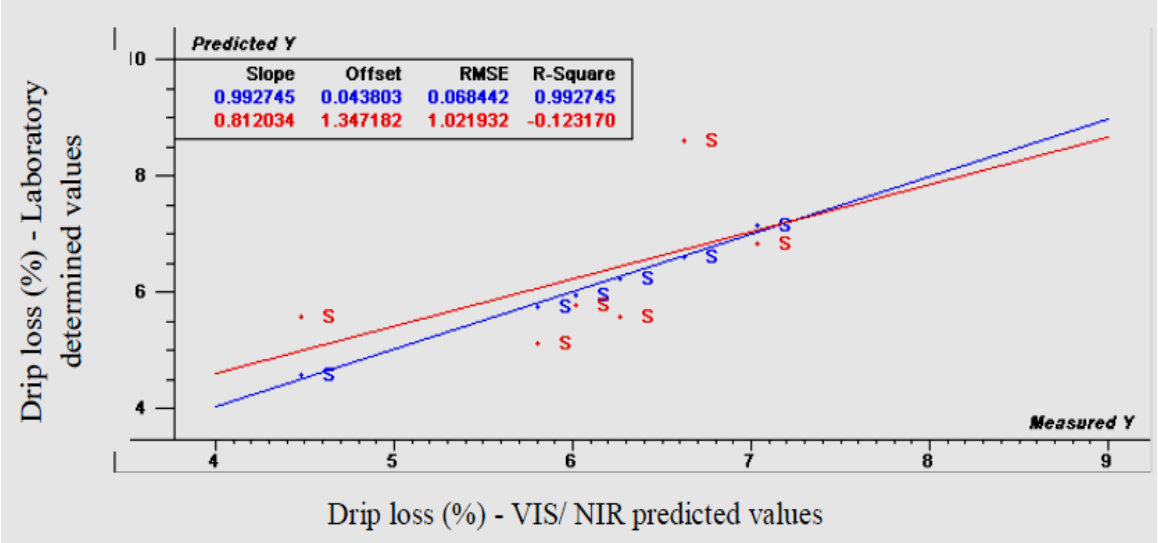

Figure 37. The relationship between laboratory determined and VIS-NIR predicted values for drip loss (%) of sever WS turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

For cooking loss, R^2_p values were 0.97, 0.73 and 0.59, RPD were 5.17, 1.74 and 2.49 and RER were 19.6, 6.38 and 7.89 for normal, moderate and severe WS respectively. The normal spectral data compatible with the regression model very well, while defect WS fillets spectral data does not fit with the same model. As a result, VIS-NIR spectroscopy is able to detect normal from defect WS turkey breast meat.

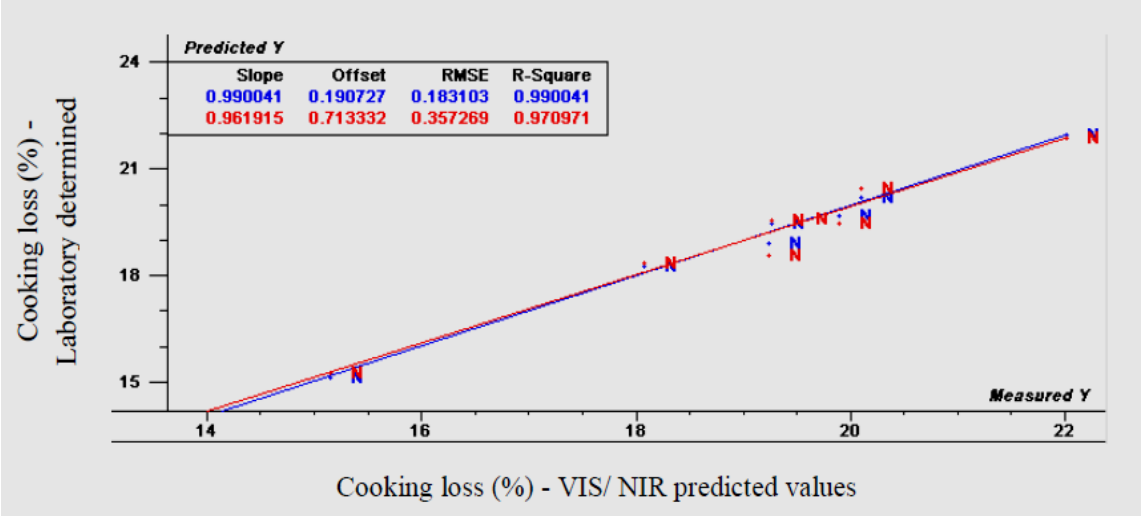

Figure 38. The relationship between laboratory determined and VIS-NIR predicted values for cooking loss (%) of normal turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

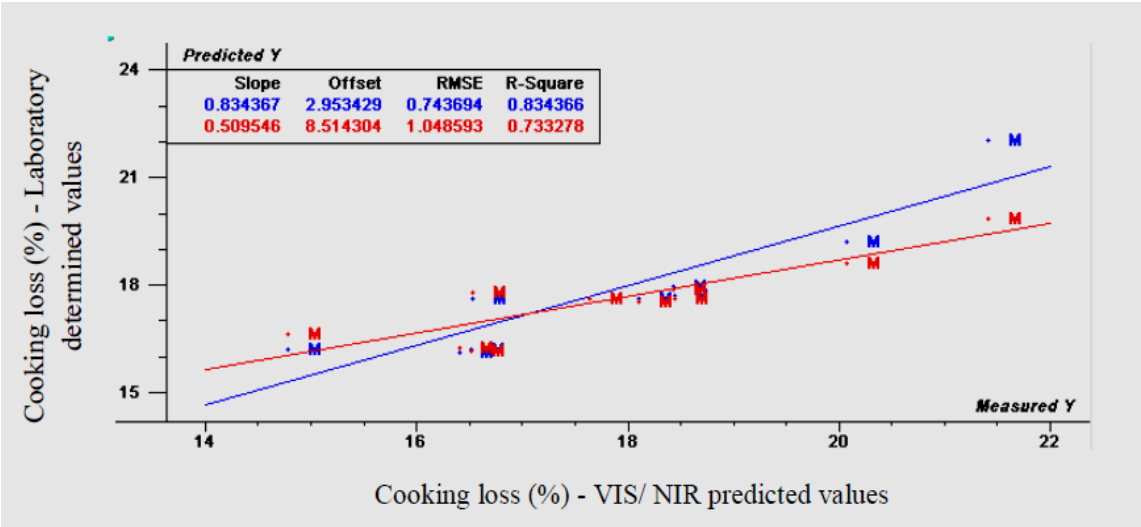

Figure 39. The relationship between laboratory determined and VIS-NIR predicted values for cooking loss (%) of moderate WS turkey breast meat using PLS for and full cross validation for 9 samples (blue line for calibration set and red line for validation set).

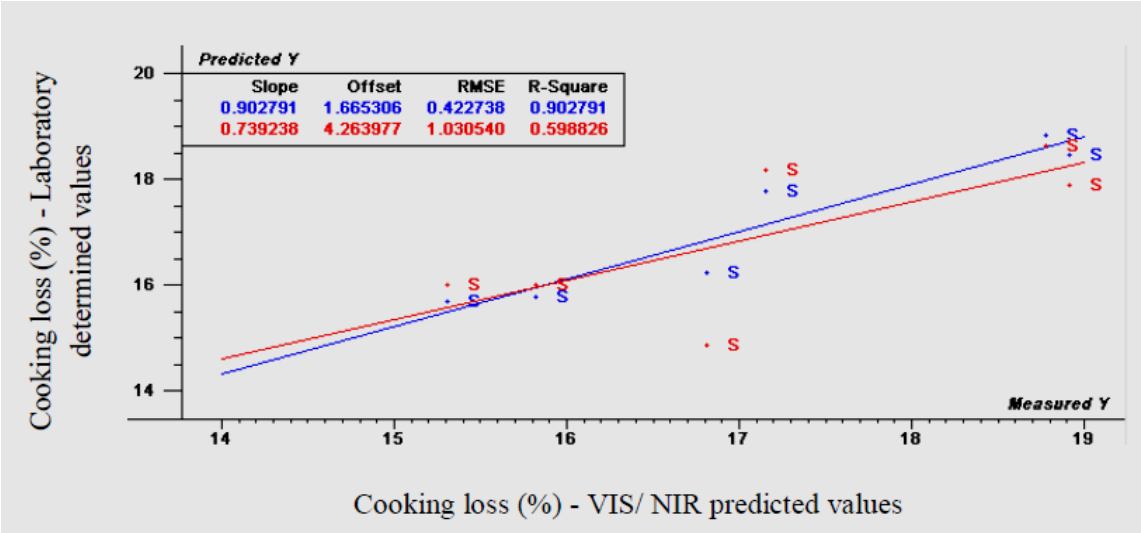

Figure 40. The relationship between laboratory determined and VIS-NIR predicted values for cooking loss (%) of sever WS turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

Calibration and full cross-validation results for proximate composition (moisture, fat, protein and ash) are presented in Table 4. The prediction values for moisture content were as the following: R^2_p were 0.86, -1.61 and -1.03, RPD were 2.67, 091 and 0.61 and also RER values were 8.48, 3.24 and 2.17 for normal, moderate and severe WS, respectively. The normal spectral data fitted the regression model very well, while WS spectral data is poorly fitted using PLS model as represented in Figures 41-43. From these results, VIS-NIR spectroscopy has the ability to differentiate normal from abnormal WS turkey fillets according to moisture content parameter.

Table 4: Statistics of the calibration equations for proximate composition (moisture, fat, protein content and ash) of the three types of turkey breast meat of the best fit and validation, including $RMSE_{cal}$, R^2_c, $RMSE_p$, R^2_p, RPD, RE and RER.

			Statistical parameters for calibration and prediction									
	Level of white striping	Preprocessing	R^2_{cal}	$RMSE_{cal}$	RPD_{cal}	RE_{cal}	RER_{cal}	R^2_p	$RMSE_p$	RPD_p	RE_p	RER_p
Moisture	Normal	SG+ SNV	0.96	0.20	5.70	0.01	18.25	0.86	0.43	2.67	0.01	8.49
	Moderate		0.27	0.78	1.99	0.01	7.06	-1.61	1.70	0.91	0.02	3.24
	Severe		0.59	0.75	1.59	0.01	5.56	-1.03	1.92	0.62	1.92	2.17
Fat	Normal	SG+ 1^{St} D	0.98	0.13	7.00	0.08	21.31	0.97	0.19	4.78	0.11	14.58
	Moderate		0.98	0.03	35.00	0.01	120.00	0.33	0.26	4.03	0.11	13.85
	Severe		0.99	0.07	15.71	0.02	48.00	0.53	0.96	1.14	0.31	3.50
Protein	Normal	SNV+ 1^{St} D	0.89	0.81	3.30	0.04	14.11	0.80	1.38	1.93	0.06	8.28
	Moderate		0.97	0.19	7.79	0.01	21.21	0.77	0.97	1.52	0.04	4.15
	Severe		0.99	0.05	31.60	0.01	105.00	0.34	1.38	0.79	0.06	3.80
Ash	Normal	SG+ MSC	0.99	0.11	10.18	0.03	32.09	0.97	0.29	3.86	0.15	4.45
	Moderate		0.50	0.16	2.62	0.08	8.06	0.61	0.51	0.82	0.26	2.53
	Severe		0.95	0.03	8.00	0.02	142.67	-2.43	0.29	0.82	0.17	2.69

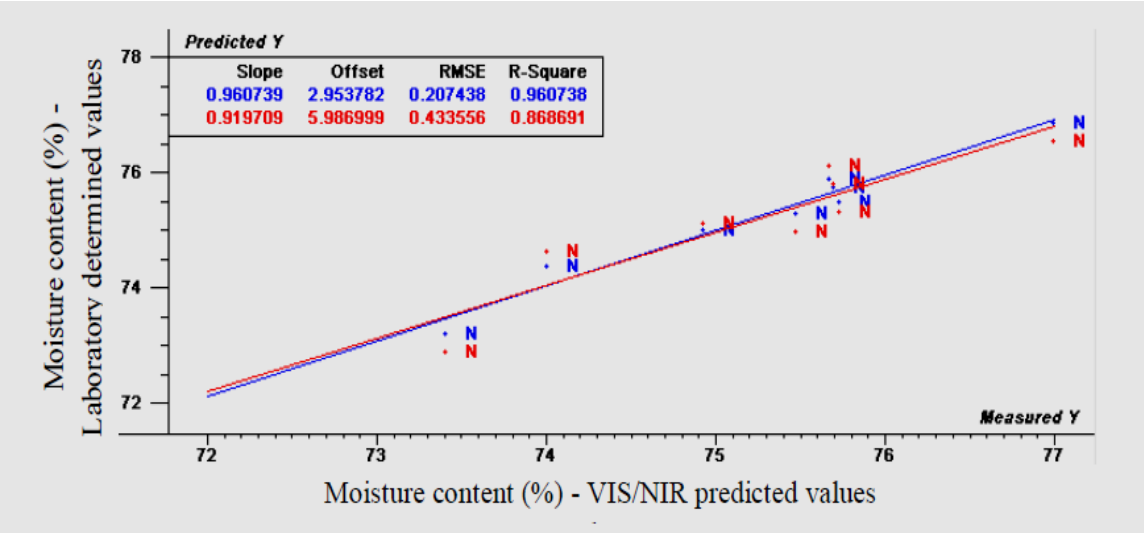

Figure 41. The relationship between laboratory determined and VIS-NIR predicted values for moisture content (%) of normal turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

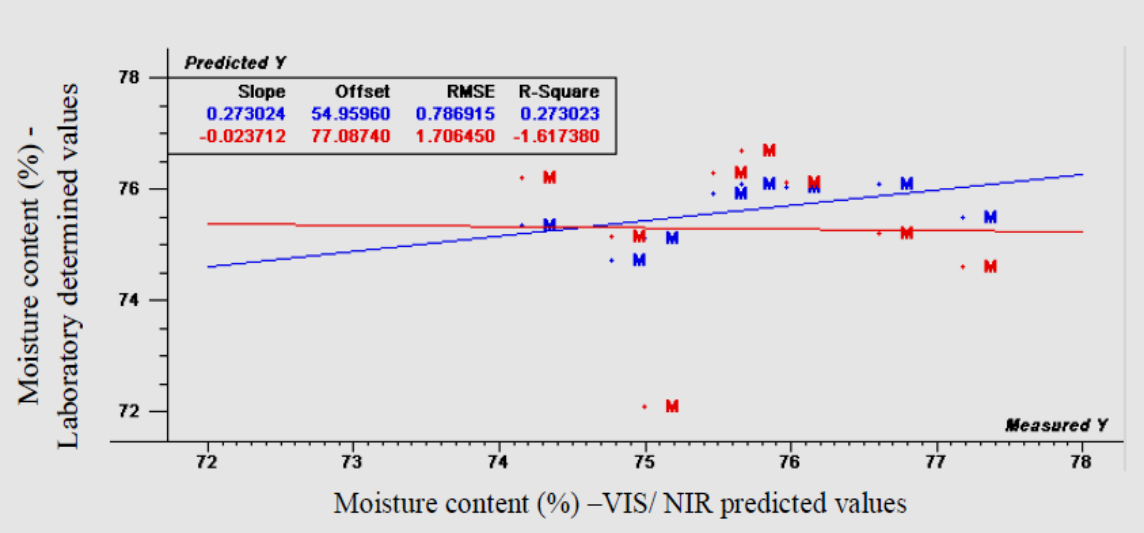

Figure 42. The relationship between laboratory determined and VIS-NIR predicted values for moisture content (%) of moderate WS turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

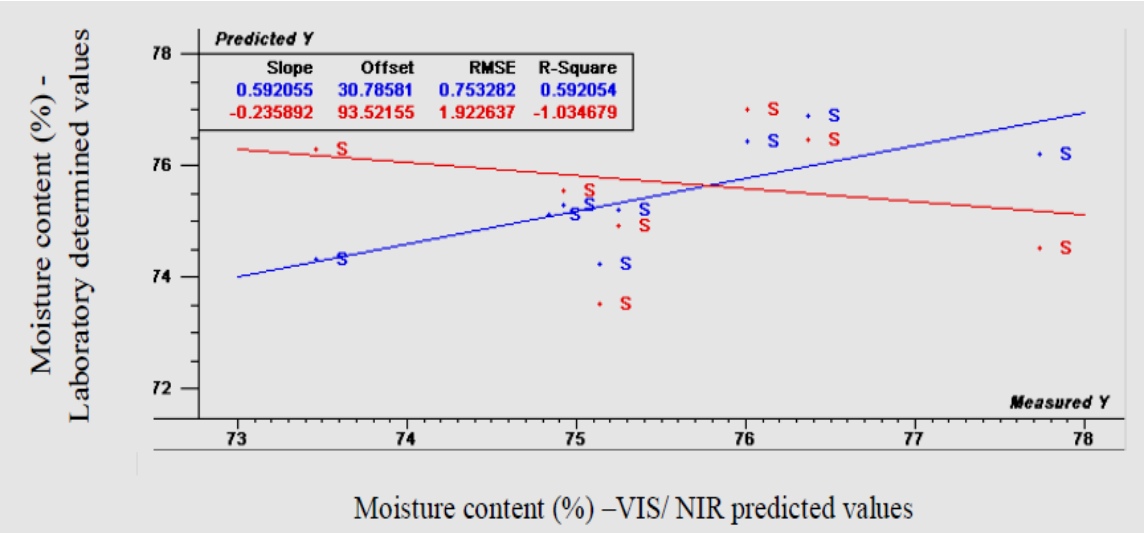

Figure 43. The relationship between laboratory determined and VIS-NIR predicted values for moisture content (%) of sever WS turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

Considering protein content, the prediction values were as the following: R^2_p were 0.80, 0.77 and 0.34, RPD values were 1.93, 1.52 and 0.79 and then RER were 8.48, 4.15 and 3.80 for normal, moderate and severe WS, respectively. The normal spectral data is relatively fitted the regression model, while WS spectral data is poorly fitted with the same model as shown in Figures 44-46.

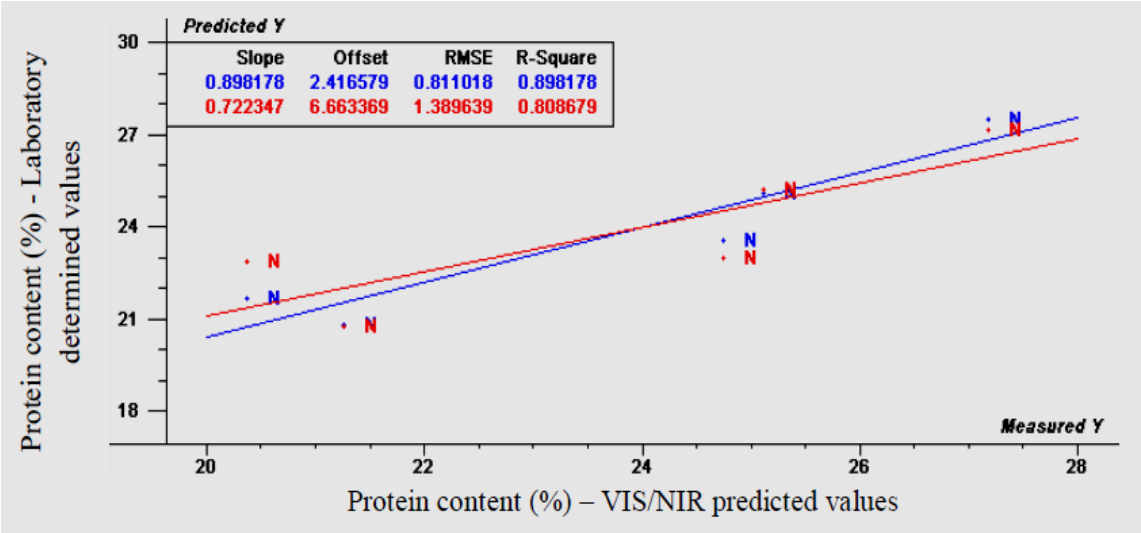

Figure 44. The relationship between laboratory determined and VIS-NIR predicted values for protein content (%) of normal turkey breast using PLS for and full cross validation for 5 samples (blue line for calibration set and red line for validation set).

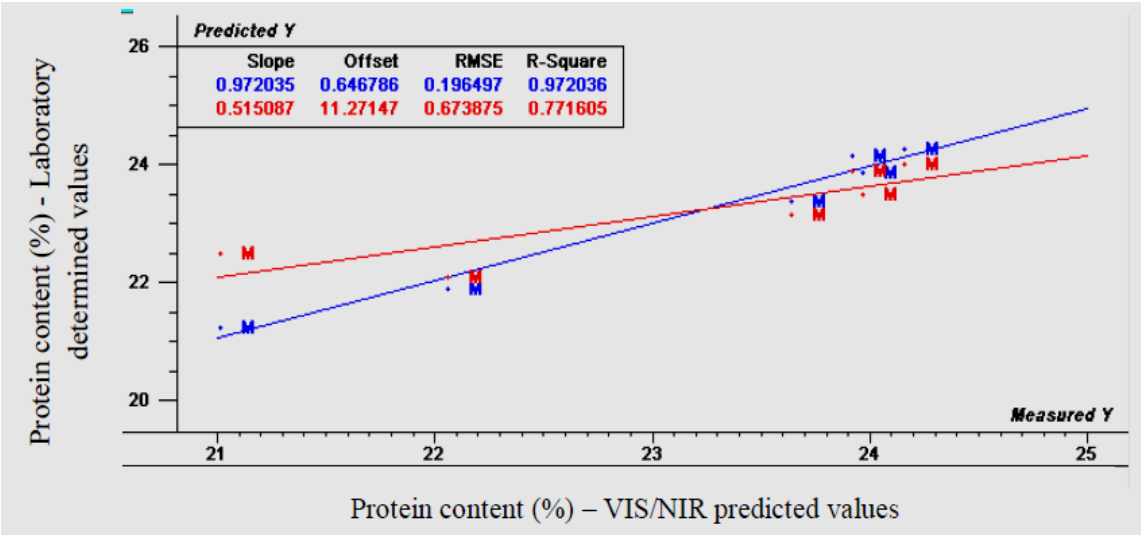

Figure 45. The relationship between laboratory determined and VIS-NIR predicted values for protein content (%) of moderate WS turkey breast using PLS for and full cross validation for 6 samples (blue line for calibration set and red line for validation set).

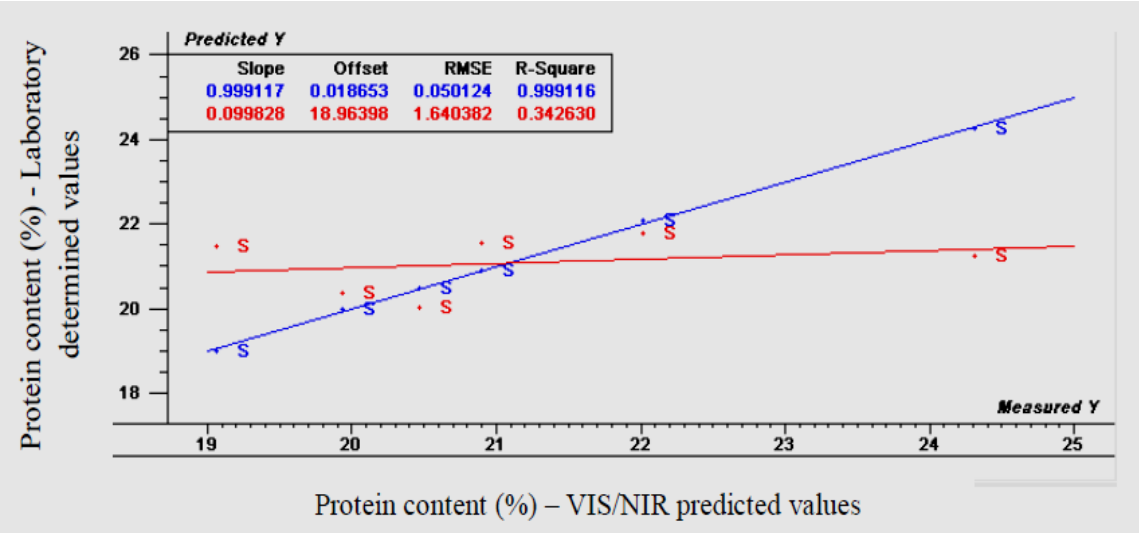

Figure 46. The relationship between laboratory determined and VIS-NIR predicted values for protein content (%) of sever WS turkey breast using PLS for and full cross validation for 6 samples (blue line for calibration set and red line for validation set).

For fat content, PLS prediction values were as the next: R^2_p values were 0.97, 0.33 and 0.53, RPD values were 4.78, 4.03 and 3.50, whereas RER values were 14.58, 13.85 and 3.50 for normal, moderate WS and severe WS, respectively. The normal spectral data is fitted with the regression model while moderate and severe WS spectral data are relatively and poorly fitted with the same regression model, respectively. The PLS prediction model for each sample is presented in Figures 47-49.

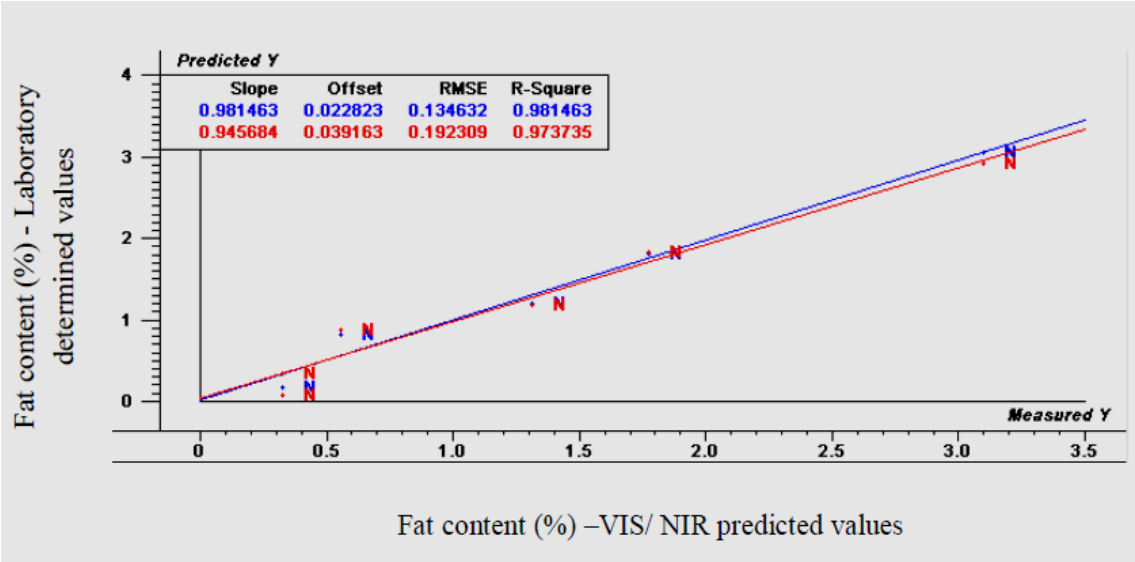

Figure 47. The relationship between laboratory determined and VIS-NIR predicted values for fat content (%) of normal turkey breast meat using PLS for and full cross validation for 6 samples (blue line for calibration set and red line for validation set).

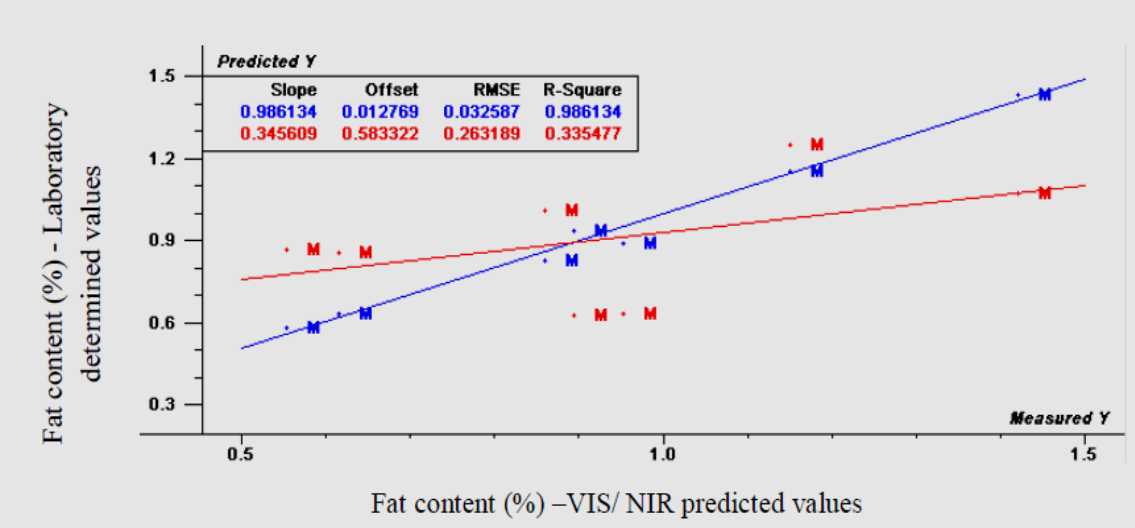

Figure 48. The relationship between laboratory determined and VIS-NIR predicted values for fat content (%) of moderate WS l turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

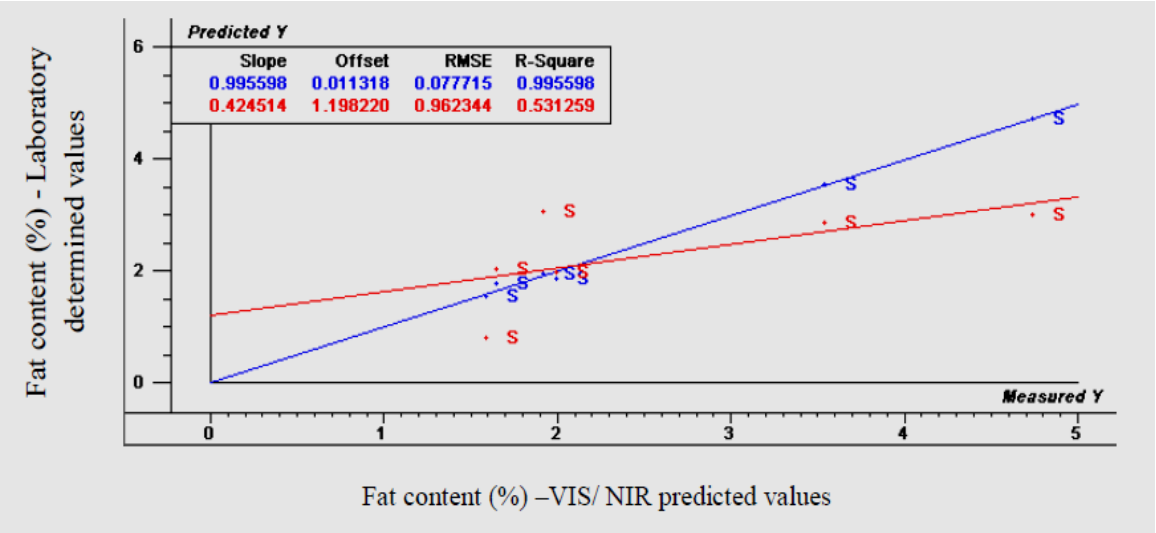

Figure 49. The relationship between laboratory determined and VIS-NIR predicted values for fat content (%) of severe WS turkey breast meat using PLS for and full cross validation for 7 samples (blue line for calibration set and red line for validation set).

Finally, for ash content, the prediction values were as the following: R^2_p values were 0.97, 0.61 and -2.43; RPD values were 3.86, 0.82 and 0.82, while RER values were 4.44, 2.52 and 2.52 for normal, moderate and severe WS, respectively. The normal spectral data is relatively fitted the regression model even that the RER value is small, while WS spectral data is poorly fitted with the same model. PLS regression plots for each group are represented in Figure 50-52. In the previously mentioned values, minus R^2_p means that the chosen model (with its constraints) fits the data really poorly.

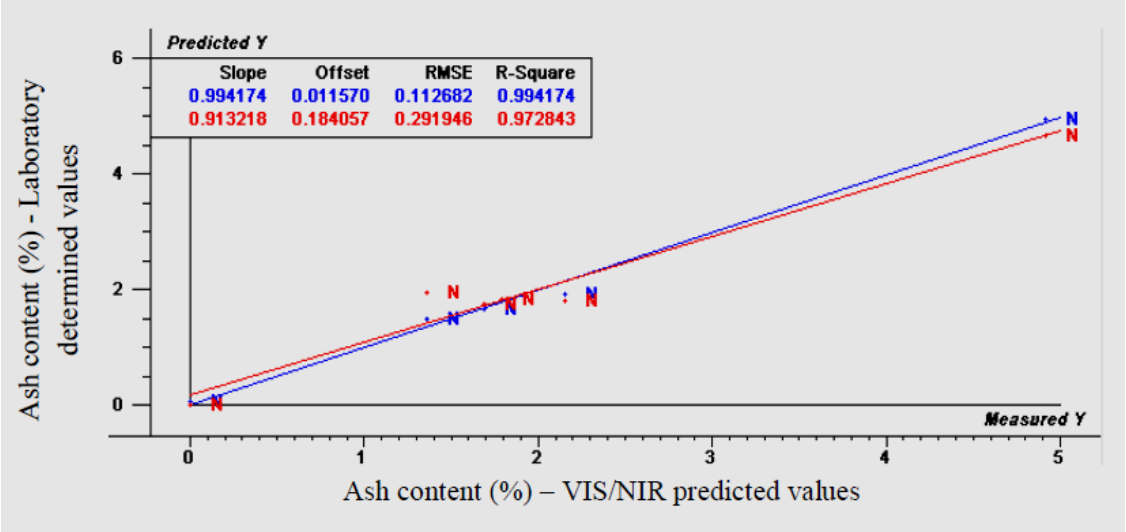

Figure 50. The relationship between laboratory determined and VIS-NIR predicted values for ash content (%) of normal turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

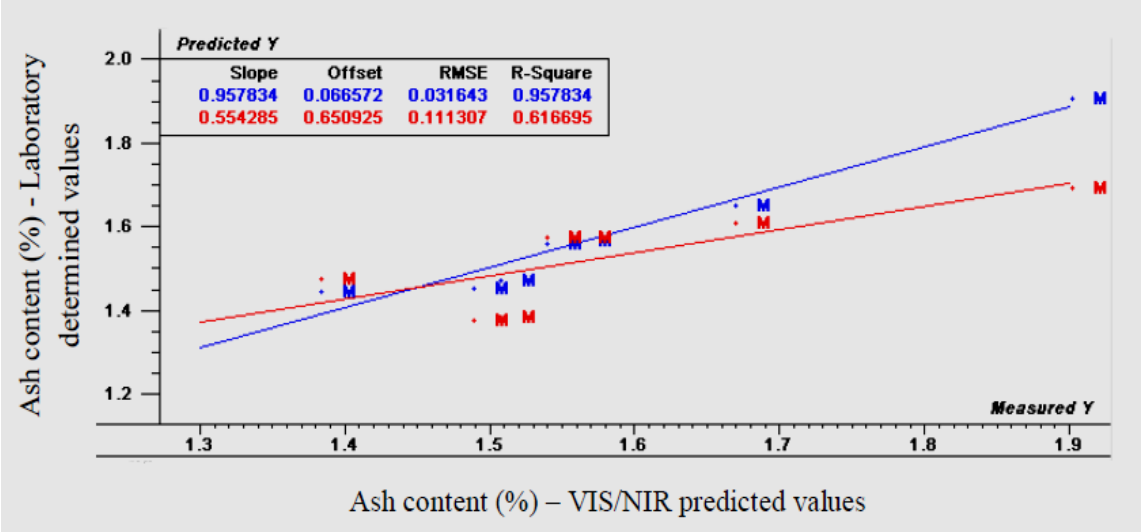

Figure 51. The relationship between laboratory determined and VIS-NIR predicted values for ash content (%) of moderate WS turkey breast meat using PLS for and full cross validation for 8 samples (blue line for calibration set and red line for validation set).

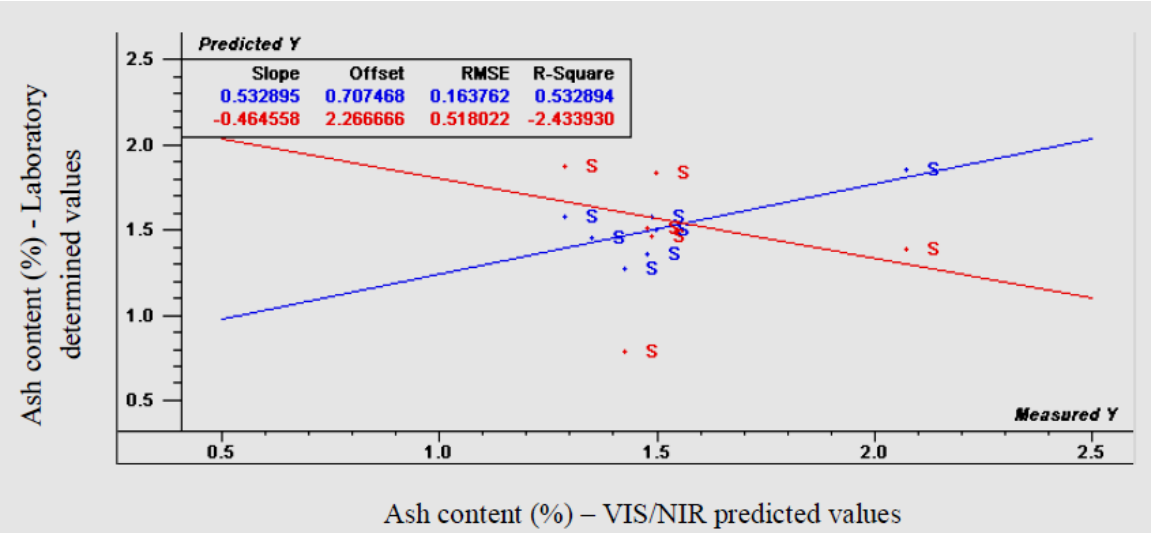

Figure 52. The relationship between laboratory determined and VIS-NIR predicted values for ash content (%) of severe WS turkey breast meat using PLS for and full cross validation for 6 samples (blue line for calibration set and red line for validation set).

6. Conclusions and Recommendation

In conclusion, the findings of this study showed that VIS-NIR spectroscopy was satisfactory to differentiate normal from severe WS turkey fillets by using several quality traits (color indexes, pH, in addition to proximate composition (fat, protein composition and ash) and water holding capacity (marinade uptake, cooking loss, drip loss and moisture content)). VIS-NIR spectroscopy was able to identify ranges in spectra that represent the chemical composition of the turkey meat. Moreover, the results open a wide door for using a portable VIS-NIR technique in the turkey industry. And it suggests the possibility of using this study for the development of an on-line sensor system.

Further study with a high number for samples is needed to confirm the ability of VIS-NIR combined MVDA techniques to differentiate normal turkey breast meat samples from defect WS.

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تمييز التشوهات العضلية (الشرائط البيضاء) في صدر لحم الديك الرومي في السوق الفلسطيني باستخدام تقنية الطيف المرئي (الأشعة المرئية والأشعة القريبة من تحت الحمراء)

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قدمت هذه الأطروحة استكمالاً لمتطلبات الحصول على درجة الماجستير في التقنيات الحيوية الزراعية

عمادة الدراسات العليا

جامعة فلسطين التقنية- خضوري.

طولكرم - فلسطين

إبريل– 2019

Abstract (In the Arabic Language)

تمييز التشوهات العضلية (الخطوط البيضاء) في صدر لحم الديك الرومي في السوق الفلسطيني باستخدام تقنية الطيف المرئي (الأشعة المرئية والأشعة القريبة من تحت الحمراء)

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الملخص

نتيجة لزيادة الطلب على لحوم الدواجن على الصعيد الدولي والعالمي، تم تحقيق تحسينات هائلة في في معدل النمو وخاصة الصدرباعتباره مصدر مهم للبروتين لهذه الطيور الداجنة. تم تعزيز هذه الإنتاجية عن طريق الانتقاء الوراثي المتعمد باستخدام التقنيات الحيوية.

كان الانتخاب الوراثي مرتبطاً بظهور تغيرات نسيجية وتعديلات كيميائية حيوية في الأنسجة العضلية لهذه الطيور، من خلال انخفاض مستوى الأوعية والشعيرات الدموية التي تقوم بالتمثيل الغذائي للأنسجة العضلية. وبناء على ذلك، فقد ظهرت العديد من التشوهات العضلية وأحدثها ظهور شرائط " خيوط " بيضاء اللون المعروفة باسم "White Strip" بالإنجليزية على صدر الدواجن.

تعتبر جميع العيوب العضلية التي ظهرت على هذه الطيور النامية وخاصة الديك الرومي مشكلة كبيرة لصناعات الدواجن؛ لأنها أثرت سلباً على سمات الجودة والسلامة لمنتوجات اللحوم. عى سبيل المثال: أثرت هذه المشاكل على المظهر الخارجي (تغيير في اللون والملمس) بالإضافة لتاثيرها على بعض الخصائص التكنولوجية والكيميائية (القدرة على الاحتفاظ بالماء، تغيير نسبة البروتين والدهون والعناصر الغذائية) للمنتج مما أدى إلى عزوف المستهلك عن شراء تلك المنتجات.

لتلافي تلك المشكلة اضطرت بعض الشركات إلى إزالة الجزء المصاب من الذبيحة من خطوط الإنتاج وتحويلها إلى لحوم معالجة أخرى مثل (قطع الدجاج والنقانق)، في حين أن الجزء المتبقي صالح للاستهلاك البشري.

فرضت الاختلافات في تكوين اللحوم بسبب زيادة تشوهات العضلات المزيد من الضغط على صناعات اللحوم لضمان الجودة. فيما يتعلق بالإنتاج وتقييم اللحوم، هناك حاجة للبحث عن تقنية سريعة،غير مدمرة وغير مكلفة.

على مدى السنوات الماضية ، استخدمت تقنية مفيدة تدعى التحليل بالأشعة تحت الحمراء (NIR) طولها الموجي يتراوح بين (700-2500 نانومتر). كما ظهر أنه يمكن التعرف على محتويات المنتج من خلال قياس كمية الإشعاع NIR التي تنعكس، تمتص، تنتقل و/ أو تتبعثر عند أطوال موجية مختلفة ومن ثم يمكن تقدير هذه المحتويات.

تقنية التحليل الطيفي NIR المستخدمة لتقييم التركيب الكيميائي للحوم ومنتجات اللحوم لديها مزايا فريدة إذا ما قورنت مع الأساليب الكلاسيكية، مثل القياسات السريعة والمتكررة، وسهولة إعداد العينات. وعلاوة على ذلك، فهي مناسبة للاستخدام عن بعد في مجال الزراعة، والصناعات الدوائية بالإضافة إلى القطاعات الصحية لتقييم سمات الجودة المختلفة. في ناحية أخرى، لا يزال التحليل الطيفي للأشعة تحت الحمراء محدودًا، حيث توجد ضرورة لطريقة مرجعية، وحساسية منخفضة للمكونات البسيطة، بالإضافة إلى التعقيد في المعايرة

بالنسبة للحوم فقد تم دراسة قدرة التحليل الطيفي NIR للتنبؤ بالعديد من الصفات النوعية لها مثل التركيب الكيميائي (البروتين، الاحتفاظ بالماء،الدهون والكولاجين)، درجة الحموضة، إلخ.

لا توجد دراسات متاحة تستخدم تقنية التحليل الطيفي لVIS-NIR للتنبؤ بالصفات النوعية لصدر الديك الرومي المتأثر بمستويات مختلفة من هذه الشرائط "الخيوط" البيضاء. ولذلك ، فإن الهدف الرئيسي من هذا البحث هو استخدام التحليل الطيفي للأشعة المرئية والأشعة الحمراء القريبة وتوظيفها من أجل التنبؤ بخصائص الجودة والتمييز بين المستويات المختلفة للعيوب الشريطية البيضاء على صدر الديك الرومي

تبعا لذلك تم اختيار 34 عينة من صدور الديك الرومي " حبش" من أصل 60 عينة بشكل عشوئي من أحد المسالخ المتواجدة في محافظة طولكرم ، تمثل مستويات مختلفة من العيوب الشريطية البيضاء (طبيعية، معتدلة، حادة). ثم تم القياس باستخدام الأشعة للعينات في مختبر جامعة فلسطين التقنية- خضوري وتسجيل البيانات للتحليل لاحقا، ومن ثم التحليل الكيمائي في مختبرات جامعة النجاح الوطنية لتقييم مؤشرات اللّون (a*، b*، و L*)، وقياس درجة الحموضة، الأمتصاص بعد النقع، فقدان السوائل بعد الطبخ، بالإضافة إلى التركيب الكيمائي(نسبة السوائل، الدهون، البروتين والرماد).

بعد استخدام برنامج لتحليل البيانات متغير المتعددات (MVDA) عن طريق تحليل كل من المربعات الصغرى الجزئي PLS، وتحليل المكون الرئيسي PCA.

أظهرت النتائج التي توصلنا إليها أن نماذج التنبؤ باستخدام PLS كانت جيدة بالنسبة للون والدرجة الحموضة والتكريب الكيمائي، بالإضافة إلى القدرة على التمييز بين العينة الطبيعية وشديدة الشرائط البيضاء.

تم تحليل بيانات VIS-NIR عن طريق PCA، وقد وجد أن المكون الرئيسي الأول (PC1) لمنطقة VIS ، NIR و VIS-NIR يفسر 98٪، 97٪ و96٪ من التغير الكلي، على التوالي. أظهر PCA أداءً عاليًا للتمييز بين اللحم العادي من غير الطبيعي (شريط أبيض معتدل وشديد).

وأخيرا، أظهرت نتائج هذا البحث أن التحليل الطيفي لـ VIS-NIR كان مرضياً للتمييز بين العينات الطبيعية من عينات الديك الرومي المصابة باعتلال الشرائط البيضاء باستخدام العديد من الصفات النوعية.

The End