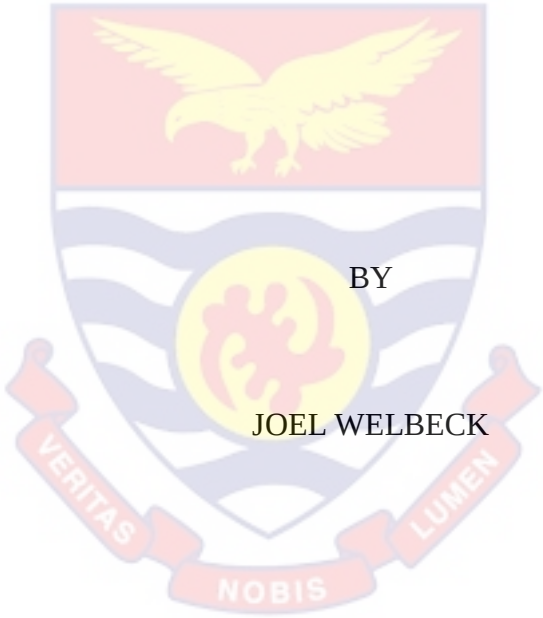
UNIVERSITY OF CAPE COAST

ASSESSMENT OF THE PHYSICOCHEMICAL AND MICROBIAL QUALITY OF GROUNDNUT PASTES FROM MAJOR MARKETS IN THE CENTRAL REGION OF GHANA AND PREDICTION OF GROUNDNUT PASTE ADULTERATION USING PORTABLE HANDHELD NIR SPECTROSCOPY WITH A MOBILE PHONE



BY

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DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my original research and that no part of it has been presented for another degree in this University or elsewhere.

Candidate's Signature: …… Date: ……..……

Name: Joel Welbeck (AG/PHP/22/0008)

Supervisor's Declaration

I hereby declare that the preparation and presentation of the thesis was supervised in accordance with the guidelines on the supervision of thesis laid down by the University of Cape Coast.

Supervisor's Signature …… Date …….

Name: Rev. Engr. Prof. Ernest Teye

ABSTRACT

Groundnut paste safety and quality is of great concern to consumers due to potential contamination and adulteration which poses serious health risk. This study investigated the safety and quality of groundnut paste using wet chemistry standard method as well as develop a novel application of hand-held NIR spectrometry coupled with chemometrics for the examination of groundnut paste authenticity and quality in real time. Samples were collected within the major markets in the Central region (Mankessim, Kotokuraba, Twifo Praso, Swedru and Kasoa). The authenticity of groundnut paste was evaluated through a physicochemical analysis and fungi count were also determined. A handheld near-infrared spectrometer was used to predict the presence of cassava flour and roasted maize flour at different percentage purity. Among the pre-processing methods used to ensure the quality and accurately of the final analysis, standard normal variant (SNV) was found to be superior. Principal component analysis (PCA) was used to extract relevant information from the spectral data set and the results showed that groundnut paste samples of different categories could be clustered. The performance of the Support Vector Machine (SVM) model shows strong predictive capabilities, with R^2 values of 0.9751 for cassava flour and 0.9753 for roasted maize flour in the training phase, indicating that it explains a substantial portion of the variance in the data. Most of the groundnut paste samples examined showed low contamination of fungi ranging from 1.60 – 2.48 log10CFU/g. The current study showed that NIR spectroscopy can classify and determine groundnut paste adulterated with cassava flour and roasted maize flour.

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DEDICATION

To Mr. and Mrs. Welbeck.

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CHAPTER ONE

INTRODUCTION

Background to the Study

The new universal economic trends and outlooks, together with advancements in food industry operations, have increased demand for high-quality foodstuffs that adhere to established legislative requirements in terms of food safety and quality. Food fraud, encompassing various deceptive practices, has permeated every food commodity, raising significant food safety alarms. Among these fraudulent acts, adulteration stands out as a prevalent form (Spink & Moyer, 2011). Manufacturers engage in this practice to enhance profits by substituting high-quality components with cheaper alternatives, thereby increasing product volume (Boadu et al., 2023). Consumer staples like groundnut paste are particularly susceptible due to their ease of adulteration. Adulterants employed include adding flour and unidentified additives to boost quantity, all at the expense of quality.

Peanut paste, commonly known as groundnut paste, is a staple food product in many parts of the world, including the Central region of Ghana. It is highly valued for its nutritional content, providing a rich source of protein, healthy fats, vitamins, and minerals (Adazebra, 2019). However, the quality and safety of groundnut paste are of significant concern due to potential contamination and adulteration. In 2015, the Food and Drug Authority of Ghana reported suspected cases of food adulteration of which groundnut paste was not exempted (Essuman et al., 2022).

Adulteration in groundnut paste can occur in various forms, including the addition of cheaper flour (cassava or roasted maize) reduces the nutritional

value and quality of the product. Additionally, the presence of contaminants such as aflatoxins, microbial pathogens, and chemical residues further exacerbates the health risks associated with adulterated groundnut paste (Essuman et al., 2022). To ensure the safety and quality of groundnut paste, there is a need to adapt effective detection methods that can detect adulterants in groundnut paste quickly and accurately (Abimbola et al., 2023).

Numerous researchers have used techniques such as chromatographic and enzymatic methods (Boadu et al., 2023)., while anion-exchange chromatography with pulsed amperometry detection is mostly preferred as the most powerful technique (Boadu et al., 2023). However, these aforementioned techniques are quite expensive, elaborate, time-consuming and often not applicable for onsite real-time analysis. Researchers have used several analytical methods to detect adulteration in groundnut pastes. Fourier transform mid-infrared spectroscopy was employed by Aykas and Menevseoglu (2021) to successfully detect adulteration in groundnut paste. Again the following equipment were used by other researchers in adulteration detection in groundnut paste; gas Chromatography with ion mobility (Tian et al., 2019) and UV-spectroscopy (Menevseoglu et al., 2021).

The use of NIR to gather information on food composition and characteristics have been reported in literature. NIR technique has been used by numerous researchers in the detection of Sudan dye adulteration in palm oil (MacArthur et al., 2020; Teye et al., 2019), coffee adulteration (Boadu et al., 2023) and rice adulteration (Teye & Amuah, 2022). NIR technology there could offer a great replacement to conventional methods used in food quality control due to its sensitivity, non-destructiveness, speed, minimal sample

preparation requirements, and lack of the use of toxic solvents. NIR data reveals itself as a potentially efficient tool for the detection of groundnut paste adulteration. This technique has been used by numerous researchers in the detection of Sudan dye adulteration in palm oil (MacArthur et al., 2020; Teye et al., 2019), coffee adulteration (Boadu et al., 2023) and rice adulteration (Teye & Amuah, 2022). Despite the numerous applications of NIR in food quality control assessments, there is paucity of information on it use in real-time detection of adulteration in groundnut paste. Therefore, considering the value of NIR in food quality control its application in detecting groundnut paste adulteration on-site could be beneficial.

Problem Statement

Despite the health and nutritional benefits of groundnut paste to humans, consumers suffer from adulteration issues. Unethical actors along the groundnut paste supply chain add cheaper ingredients like cassava flour locally called “Kokonte” or roasted maize flour into groundnut paste to increase profit. This dilution compromises the quality and safety of groundnut paste.

This adulteration practice introduces contaminants hence, decrease consumer trust. Also, Essuman et al., (2022), testified that groundnut paste is the third most adulterated food product on the Ghanaian market. Again, in 2015 the Food and Drug Authority of Ghana reported some suspected food adulteration cases of which groundnut paste was not exempted (Essuman et al., 2022). Several techniques have been employed in the detection of adulteration in groundnut paste. Traditional techniques such as laboratory analysis are time-consuming, destructive and less effective in their application. Therefore,

there is a need to adopt a rapid technique that can detect adulteration on-site. In view of these, this study sought to assess the safety and quality of groundnut paste in the central region of Ghana using handheld portable NIR spectroscopy.

Implication of the Study

Policymakers in groundnut paste-producing nations in charge of preventing groundnut paste adulteration instances have been slow to catch up with the fraudsters. Since the 2015 revelation by the Ghana Food and Drug Authority (FDA) about the contamination of groundnut paste with flour, consumers have remained concerned about its persistent recurrence. Most crucially, authorities have been reluctant to gather information on current groundnut paste adulteration before it reaches consumers. This could be related to the costly and time-consuming characteristics of the wet chemical processes employed. These methods necessitate elite laboratory trials, meticulous sample preparation, and well-trained people. Furthermore, due to the lengthy and laborious characteristics of the detection techniques utilised, only a few samples could be analysed at a significant cost, implying that the safety of groundnut paste on the market cannot be assured (Essuman et al., 2022). HPLC + UV diode array detection and other wet chemistry methods are well-established analytical techniques for detecting food adulteration (Teye et al., 2019). Masaka and others used High-Performance Liquid Chromatography (HPLC) to pinpoint contamination and adulteration of peanut butter (Masaka et al., 2022). Also, a report from Zhang et al. (2015), used Ultra Violet visible spectroscopy to determine the adulteration of peanut butter oil. Nevertheless, these approaches have their drawbacks that do not favour

their use in under-developed nations. These techniques take time, are costly, and are arduous, necessitating the use of a laboratory with specific equipment, involving chemical use and detailed sample preparation. Hence, there is a need for other alternatives and near-infrared spectroscopy could be highly useful. NIR spectroscopy is a cutting-edge technology with manifold advantages: it is rapid and utilises no chemicals, making it ecologically safe. Developments in computer and electronics technology have made NIR spectroscopy equipment more portable and usable in a variety of disciplines. A portable NIR spectroscopy approach, in particular, has been utilised to examine the adulteration of various food products: Boadu et al. (2023) classified and verified coffee adulteration with coffee husk by adopting a portable NIR spectroscopy. There are many reports concerning the usage of NIR spectroscopy to identify Sudan (IV) dye in chilly powder Haughey et al. (2015), and fluorescence spectroscopy to detect the legitimacy of walnut oil as reported by Li et al. (2015). Yet, there has been inadequate information or no research on detecting cassava flour or roasted maize flour in groundnut paste utilising hand-held NIR spectroscopy and chemometrics. In the context of ongoing groundnut paste adulteration, investigating the viability of a swift and low-cost detection tool using a hand-held NIR spectroscopy would be extremely beneficial and well-timed.

General Objective

The main objective of the study is to assess the physicochemical properties, microbial safety using wet chemistry method and predict the authenticity of groundnut pastes using portable handheld NIR spectroscopy coupled with smartphone.

Specific Objectives

1. To investigate the physicochemical properties of groundnut paste sold in the Central Region of Ghana.
2. To investigate the microbial quality of commercial groundnut paste sold in the major markets in the Central Region.
3. To predict the integrity of authentic groundnut paste using portable NIR spectroscopy coupled with a smartphone.

Organisation of the Study

The five separate chapters that make up this study's structure each focus on a different facet of the research process. The study's introduction is given in Chapter 1 contains the research background, the problem statement, the study's relevance and specific objectives. The second chapter provides a thorough assessment of the literature, looking at previous research and hypotheses that are pertinent to the subject of the study. It highlighted the gaps that this research attempts to fill and established the theoretical framework for the investigation. The study's experimental design is covered in full in Chapter 3. It describes the methods that were used, such as the research strategy, methods for gathering data, and steps taken to guarantee the validity and dependability of the conclusions. The analysis of the data gathered is the focus of chapter four. It starts with the results being presented and ends with a detailed explanation of the findings in light of the study questions and hypotheses.

The study's main conclusions are outlined in Chapter 5, along with recommendations for additional research and real-world applications. It considers the study's consequences for the larger field of study as well.

CHAPTER TWO

LITERATURE REVIEW

Introduction

This chapter presents a review of related literature on the safety and quality of groundnut paste adulteration in Ghana. It presents related literature on Issues and Challenges of Food Safety, Food Safety Control Systems, Consumer's Position Regarding Food Safety, Groundnut Production, Global production of groundnut, Local production of groundnut, Import and Export of Groundnut, Other Economic Benefits of Groundnut Production, Groundnut paste processing procedures, Quality and Safety Attributes of Groundnut paste, Aflatoxin infection on Groundnut and Groundnut paste, Food Fraud, Types of food fraud, Food fraud incidents and their ranking, Food adulteration and its impact on safety, The impact of food adulteration on both consumers and producers, Food Safety Initiatives in Food Products, Application of NIR Spectroscopy and Chemometrics in the Detection of Adulteration and Chemometrics.

Regardless of advances in science and technology, there is still a major problem with food safety around the world due to the presence of food-related vulnerabilities. The manufacturing of food that has been processed or partly processed has taken the place of traditionally produced cash crops and raw materials. New hurdles have emerged in the food supply chain as an outcome of this transformation, including an upgrade in food regulation and the existence of numerous groups addressing food safety issues. Under-developed nations including sub-Saharan African nations must learn to adopt the new trends in the global market regarding food safety standards to overcome the

escalating hurdles in the market (Epelboin et al., 2014). Despite the increasing complications of the food chain, the risk to food safety persists. Emerging threats, such as the presence of harmful adulterants like Sudan dye, pose a continuous risk to human health in food products. This risk is exacerbated by the widespread distribution of food, often occurring far from the locations of initial production, processing, and packaging.

Issues and Challenges of Food Safety

The landscape of global food production, processing, and distribution has evolved, presenting new challenges for food safety. In the contemporary era, food produced in one country can easily traverse borders, being both imported and exported to be consumed in various nations. The growing global population's desire for a diverse range of foods has fueled an increase in international trade. Consequently, this surge in global trade accelerates the potential transmission of foodborne pathogens from one nation to another. There is more time between food processing and consumption, which increases the risk of food contamination. Foodborne infection outbreaks have increased as a result of lifestyle changes and consumer demands for foods outside the home. Furthermore, consumer’s rising interest in international cuisine may be an unanticipated source of food-borne illness as reported by (Epelboin et al., 2014).

Although urbanization in underdeveloped nations is raising awareness about food safety issues among consumers, the level of awareness remains relatively low among consumers in sub-Saharan Africa. In contrast to affluent countries, there is a subdued demand for safe food among consumers in underdeveloped nations. As indicated by Ortega and Tschirley (2017), a

staggering 85% of the 900,000 children under the age of 10 who succumbed to diarrhoea in 2009 were from underdeveloped nations(Ortega & Tschirley, 2017). The concerns in underdeveloped nations are not limited to health-related issues alone; there is an escalating worry about food fraud, adulteration, and the presence of feed additives and pesticide residues. In 2017, Ortega and Tschirley highlighted that consumer awareness of food safety issues in emerging nations is expected to rise due to rapid population expansion and increasing income levels.

As income and education levels increase in developing countries, there exists a notable opportunity to enhance food safety standards and regulations (Reardon & Chen, 2012; Tschirley et al., 2013). Achieving this improvement relies on the willingness of supply chain participants to modify their behaviour and effectively address the growing customer demand for food safety. These participants must be attuned to consumer needs and their willingness to pay for enhanced food safety measures. Over time, consumers are likely to elevate their standards for food quality assurance, resorting to various measures to ensure the safety of the food they purchase. This may involve visually inspecting food products to assess their freshness and the hygienic conditions under which they are marketed.

Food Safety Control System

Most food testing is done on the finished product after it has been through all the other units of operations. To reach the probable outcome, procedures must be controlled as well as imported food products and ingredients. This means moving away from end-product analysis. The RASFF primarily found food contamination problems in the food item's finished

products. It is generally acknowledged that sampling food items' final products for analysis is to look for hazards which is an inadequate method of ensuring the safety of the food item put on the market (Nguz, 2007). Therefore, food samples should be examined to confirm their authenticity along the entire food continuum. This can be done more effectively by collaborating with the food sectors. The nation's food safety officials can aggregate the data produced by these analyses for a programme to monitor food safety as being done by the European Union.

Other countries like the United Arab Emirates, have created food control systems to monitor and regulate both domestically produced and imported food utilising risk management (Elmi, 2004). This country uses mobile devices and specialized software to increase the safety of food items, predominantly for high-risk foods. For their food products, nations like Sudan and Egypt have followed the Codex criteria for food safety. Consumers, researchers, policymakers, the government, and the food sector are however concerned about food safety. Significant efforts in control measures and assurance systems in many food sectors throughout the globe have been made as a result of raised consumer awareness and new governmental demands on food production systems (Joint, 2001; Khatri & Collins, 2007).

One of the primary issues with food safety is to focus on exports of food items from underdeveloped countries to developed countries. This has led to a lack of focus on educating people about the financial costs associated with improper food safety measures in the local food systems of underdeveloped countries. Therefore, it is unknown how consumer and

producer behaviour in terms of food safety varies with economic development level.

Consumer's Position Regarding Food Safety.

Consumers wield significant influence over the safety standards of food products as the ultimate end users. They possess the right to actively engage in the risk assessment of a food product and, importantly, the right to be informed about the items they intend to purchase from the market. Empowering consumers with the ability to make informed decisions is crucial in ensuring food safety standards align with their preferences and expectations. When the process of evaluating the risks associated with food products is transparent and free from corporate and governmental involvement over the total risk that consumers feel acceptable, this will become practically feasible. The mainstream of food products is not presently scrutinized, which fallout in the market being filled with inferior and unclean food items (Nguz, 2007).

Consumers are gradually turning to supermarkets for their fresh produce purchases due to food contamination and adulteration in the open market (Moustier et al., 2010; Reardon et al., 2012). Mergenthaler et al., (2009), provided evidence that supermarket purchases of fruits and vegetables are more elastic in terms of income and price than purchases of fresh produce in open air-markets. Furthermore, Ortega and Tschirley (2017) discovered that although consumers viewed the safety and quality of food to be crucial retail elements for both supermarkets and open markets, supermarkets are perceived as being more advantageous in this regard. In other words, people are willing to spend more on high-quality and healthy food.

Groundnut Production

The scientific name for groundnuts, *Arachis hypogaea*, commonly termed goober or earthnut, are grain legumes that are mostly grown for their edible seeds. Records of its cultivation date back to 1500 BC (Smartt, 2012). After soybeans, cottonseed, and rapeseed, it is the world's 4th most important oilseed crop and the 13th most vital food crop. It is massively cultivated in the tropical and sub-tropical climates. Worldwide, earthnuts are grown, particularly in under-developed nations where they account for approximately 94% of global production and around 97% of all farm acreage (Nkansah et al., 2021a).

Global production of groundnut

Groundnuts are cultivated in numerous nations all over the globe. Groundnuts are grown massively in China, the US, Africa, South Asia, Southeast Asia, South America, and Mexico, according to a report from the US Department of Agriculture (USDA, 2018). According to the survey, China is the world's top producer of groundnuts. After India, Nigeria is the third-largest producer of groundnuts globally and the top producer in Africa (Chakuri, 2018). In line with reports from the 2015–2016 production season, the average groundnut yield worldwide was 1.63 MT/ha, and preliminary estimates for the 2016–2017 production season put it at roughly 1.70 MT/ha (Chakuri, 2018).

Local production of groundnut

Ghana ranked 17th in the world in 2017 for groundnut output, with an approximate yearly production of 420,000 tonnes (Nkansah et al., 2021a). Ghana's northern region produces more than 90% of the nation's groundnuts. It

is Ghana's most significant legume crop. According to a 2008 poll, 80% of Ghanaian respondents ate groundnuts or their products at least once a week, while 32.0% of respondents consumed them three times a week (Nkansah et al., 2021a).

Import and Export of Groundnut

Exports of groundnut merchandise can be found in various forms, including shelled, unshelled, and processed varieties. Groundnuts are processed in multiple ways, including crushing them for oil and producing food ingredients like peanut butter and chocolate. Before being exported, shelled groundnuts may also undergo minor processing, such as toasting them easily for snacking (Nkansah et al., 2021b). According to (Nkansah et al., 2021b), The Caucasian market is projected to be the world's massive importer of peanut foods. The Netherlands is thought to be the biggest importer in Europe, making up over 44% of all imports into the continent in 2015. Since 2011, the Netherlands has seen an annual increase in the volume and value of groundnut imports of 1.5% and 6.3%, respectively. Spain, Poland, Italy, Germany, and the United Kingdom are important European importing markets. Argentina, China and Brazil are the primary exporters of groundnuts to European markets from under-developed nations. It is also known that groundnuts are heavily exported to European markets from Egypt and Nicaragua. With 44% capacity of the three hundred and thirty- eight thousand tonnes of groundnuts imported into part of Eurasia in 2015, Argentina is the biggest supplier of earthnuts to the Caucasian market. As a percentage of the total supply in 2015, the following exporting nations were recognised to have provided peanuts to Europe: China (7.9%), Brazil (5.2%), Nicaragua (3.1%),

and Egypt (1.6%). Since they account for more than 60% of global groundnut exports, it is noted that the under-nations are the primary exporters of the crop. With roughly 15% of the total groundnut exports to Europe in 2015, the USA is the second-largest global supplier of groundnuts and the top supplier among developed nations. Other developing nations that have seen a notable surge in groundnut exports over the last six years, along with corresponding increases in their yearly growth rates, include Ghana (148%), Vietnam (27%), and Chile (104%). It is important to highlight that these nations only supply between 30 and 300 tonnes of groundnuts annually to the European market. However, groundnut exports have decreased due to China's current development in groundnut industrialization. Reports show that over the past ten years, groundnut exports have nearly halved to 500,000 tonnes, while imports have increased by nearly 50% in China. Ghana is an underdeveloped nation whose groundnut export to the Caucasian market is regarded as negligible, with its supply rate increasing by approximately 145% over the previous five years (Nkansah et al., 2021b). China's position in the import and export of groundnuts benefits tiny exporting countries such as Ghana. Ghana has an ideal atmosphere and resources for producing groundnuts. Despite the advantages mentioned above, which could increase Ghana's impart on peanuts to the Caucasian market. Due to aflatoxin contamination, Ghana’s earthnut product supply to the EU will be at risk of rejection. The European Commission undertook a detailed assessment of groundnuts manufactured in Ghana, which found this. The examination found that the majority of the items included an increased level of aflatoxin, making them unsuitable for the worldwide marketplace (Omari et al., 2020). According to the article, the

Ghana Export Promotion Authority (GEPA), in collaboration with the Trade Related Assistance and Quality Enabling Programme (TRAQUE) - Caucasian Union Agency, has launched a capacity-building project to sensitise actors in Ghana's groundnut food chain to reduce aflatoxin infestation. According to Omari et al., (2020), Ghana's non-traditional export yielded a revenue of 2.5 billion dollars, with peanuts accounting for US$6.4 million in 2013. The Ghanaian government has set a target of raising five billion dollars in foreign earnings from international exports by 2019, with groundnuts expected to be the major contributor.

Other Economic Benefits of Groundnut Production

There are numerous more economic advantages of groundnuts than the foreign exchange profits a nation receives from their production. For instance, research shows that similar to other sub-Saharan African nations, groundnuts are both a commercial crop and a source of sustenance in northern Ghana (Ibrahim et al., 2012). The economic importance of peanuts is categorised below:

Agronomic Importance: A leguminous crop, groundnuts fix atmospheric nitrogen into the soil in the same way as other leguminous crops (Tsigbey et al., 2003). This boosts the soil's nutrient content, which qualifies the crop for a crop rotation technique on a given plot of land. Additionally, the immediate effects of winds and precipitations, which can cause erosion, tend to be mitigated by the vegetative cover.

Income generation: Groundnut is a cash crop for farmers in Ghana, particularly North Ghana, where it is primarily grown in massive amounts(Ibrahim et al., 2012). Producers receive most of their income from

the sale of groundnut products, which are primarily produced as unshelled or shelled nuts. One-time value chain participants receive groundnut income in the form of profits from activities carried out. The majority of groundnuts grown by farmers in Ghana are sold out.

Employment: Many people are employed across the value chain of peanut production. Like any other crop, groundnuts have a value chain that begins with production and continues through several steps to get the product to the end user. This results in the employment of actors at every level of the value chain. In Northern Ghana, groundnut production is a small activity for male producers but a big vocation for females. Another step in the groundnut value chain that creates jobs for the chain's participants is the distribution of nuts. According to (Owusu-Adjei et al., 2017), retailers, wholesalers, and assemblers are examples of distributors in the value chain. They observed that the majority of groundnut processors are female and that they work in the industry.

Manufacturing food ingredients for industries: The industrial manufacturing of food products and their consumption drive the importation of peanuts into the Caucasia markets. In addition to the industrial extraction of oil, peanuts are used to manufacture a wide variety of other food products in Europe, such as peanut butter and chocolate (Guteta, 2017). Several other innovative items, including "drinkable peanut powder," "plus Bami Goreng with Satay Ajam," Magnum Double Groundnut Butter Ice Cream, and Groundnut Milk products, have also been discovered in the European markets. It's reported that flavoured peanuts with extra coating texture are becoming popular as a snack in Caucasian marketplaces. In Ghana, peanut snacks like

"Nkatie Burgers," made by Fabricade Pelo: Burger Food Industries in Taifa-Accra, are quite popular.

Nutrition: From another angle, groundnuts provide nourishment. For instance, as mentioned by (Taphee et al., 2015), it can be consumed by boiling or roasting. In Ghana, roasted plantain or banana is occasionally consumed alongside roasted groundnut. Freshly harvested, boiling groundnuts are frequently seen in markets bundled in rubber bands or stacked in pans for sale. Additionally, groundnuts can be prepared in many ways and consumed on their own or in combination with other foods. It can be mashed into a paste and utilised in a variety of ways, such as making soup, making butter to spread on toast, extracting oil locally, and processing it further to make cake and powder, which are known locally as kuli and kuli Zim, respectively (Ibrahim et al., 2012).

Groundnuts contain the majority of food nutrients in the following proportions: 20% carbs, 25% protein, and 50 per cent high-quality edible oil, they are thought to help fight food and nutrition insecurity. Together with vitamins E, K, and B, it also includes minerals including phosphorus, calcium, magnesium, and potassium (Girei et al., 2013).

According to reports, groundnut is the 13th most essential food crop worldwide, the 4th oilseed crop, and the 3rd most vital source of vegetable protein after soybean (Taphee et al., 2015).

Derived-Products: Peanut products include the haulms that are left over after the nuts are harvested, the shells that are left over after the dried groundnuts are shelled, and the cake that is left over after the oil is extracted (Ibrahim et al., 2012). They pointed out that two goods—haulms and cake—are crucial

components of animal feed. The previous author claims that farmers occasionally sell the haulms (fodder) that are mistakenly thought to be hay in urban markets to supplement their income. Alternatively, they may utilise them to feed their ruminants. The cake is a crucial component of poultry feed, providing the birds with a supply of protein along with additional minerals and vitamins.

Groundnut paste processing procedures

Shelled groundnuts are graded and cleaned to separate sound, high-quality kernels. The right amount of roasting is then applied to the nuts to generate the desired flavour. When producing groundnut paste, the roasted groundnuts are crushed along with their skins, however, occasionally the skins are removed. The paste is a staple of groundnut soup, a popular and frequently consumed meal in Ghana and across West Africa. Its batches are cooked over an open fire made of wood. Rotating drums are typically used by commercial processors for roasting. Electricity, propane gas or wood can all be used as the heating source. It produces uniform roasting because the temperature and heating time control is greater than with small processors' methods. As a rich source of protein for numerous populations worldwide, groundnut paste is made up of peanut oil distributed in fine groundnut solids, which are mostly attained by grinding groundnuts after they have been roasted (Nkansah et al., 2021a).

Quality and Safety Attributes of Groundnut paste

Moisture content is one vital factor in the groundnut paste industry (Kandala et al., 2008). Managing the amount of moisture is crucial during processing (McDaniel et al., 2012). It significantly impacts the sensory

attribute of the product, resulting from chemical reactions and drying during roasting (Lee & Resurrection, 2006). Proper moisture control is essential for maintaining stability and quality in roasted peanut products and preventing food-borne illnesses like Salmonella contamination in low-moisture items (Podolak & Black, 2017). Peanuts and groundnut paste are recognized for their nutritional content (Settaluri et al., 2012). Ironically, Barberis et al., (2012), reported that this nutritional richness also creates a favourable environment for microbial development and mycotoxin infection. Quality issues related to groundnut paste include food safety concerns like Salmonella outbreaks and the deterioration of physicochemical attributes (Burnett et al., 2000). Due to their high oil content, groundnut paste and groundnut butter are prone to rancidity and off-flavors resulting from lipid oxidation. Also, Li et al., (2013), reported that lipid oxidation is a common method for assessing oxidative rancidity in oils and fats. Peroxide value (PV) measures the concentration of peroxides formed during the early phases of oxidation. Researchers have used PV as an indicator to evaluate the storage stability of earthnut products, including products of oilseed from sunflower (Muttagi et al., 2014), peanut butter(El-Rawas et al., 2012), and shea butter (Honfo et al., 2011).

Aflatoxin infection on Groundnut and Groundnut paste

A significant microbial concern related to legumes involves managing mycotoxins produced by fungi like *Aspergillus flavus and Aspergillus parasiticus.* Aflatoxin contamination can occur at various stages along the food chain. Earthnuts are particularly susceptible to fungal infection during and after harvest processes, handling and storage, putting them at the peril of

aflatoxin infection (Mutegi et al., 2012; Villa & Markaki, 2009). Peanuts serve as a favourable substrate for *Aspergillus sp* growth and aflatoxin production (Bakhiet & Musa, 2011). Mycotoxins, formed by fungal species, have immunosuppressive impacts. Epidemiological surveys reveal an optimistic relationship between aflatoxin consumption and liver cancer prevalence (Humans et al., 2002). Among the various types of aflatoxins, B1 and B2, G1 and G2 are unexceptional and significant, causing human diseases. Aflatoxin B1, the most widespread and toxic form, poses particular health risks (Kamika & Takoy, 2011; Wild & Gong, 2010).

When earthnut is infested with aflatoxin, there is a significant danger to consumers who consume groundnut paste processed from such earthnuts (Mutegi et al., 2012). Nigam et al., (2009) reported that Individuals with weakened immune systems are more susceptible to aflatoxin-related infections. When Hepatitis B or C are combined with any viral illness consuming highly infested food can lead to increased mortality among patients with compromised immune systems as a result of exposure to aflatoxin.

Several nations have established laws that set extremely acceptable restrictions for aflatoxin in food matrices. These limits are typically in the low micrograms per kilogram range (Chijoriga, 2017). 2 forms of restrictions occur: 1 for aflatoxin B1 (5 µg/kg) and another for the total of the 4 aflatoxins (B1, B2, G1, and G2) (5 µg/kg) (TZS 844:2014). High-Performance Liquid Chromatography (HPLC) coupled with fluorescence detection is commonly used for aflatoxin examination (Spanjer et al., 2008; Vega, 2005). HPLC with fluorescence detection is particularly accepted due to its low limit of quantification, and accuracy (Bao et al., 2010).

Groundnut pastes are multipart mixtures containing nutrients, minerals and various inorganic components. During the processing of groundnut paste using solvents, many of these constituents co-extract with aflatoxins. To accurately quantify parts per billion levels of aflatoxins, a thorough sample cleanup protocol is essential. This involves removing matrix components through techniques like immunoaffinity columns (IAC) or solid-phase extraction (SPE) (Countryman et al., 2009).

Food Fraud

Manning and Soon (2016)**,** defined food fraud as any intentional modification, distortion, or mislabelling of any food product along the food supply chain. Food fraud is described as "deliberately introducing food on the market, for financial gain, to deceive the consumer" by the Food Standards Agency (FSA) (Elliott, 2014). Food fraud occurs when food does not meet legal requirements. Food fraud can occur anywhere, including the raw material, an ingredient, the finished product, and the packaging of the food. Although the majority of food fraud is not hazardous, there are notable exceptions, such as melamine in Chinese skimmed milk powder (Gossner et al., 2009), Sudan dyes in spices (Stiborová et al., 2002) and fabricated labels of puffer fish as monkfish (Cohen et al., 2009).

Elliott (2014), defines food fraud as an act planned by individuals to defraud and harm people who purchase and consume food. Food crime is an act when food is intentionally tampered with to damage people or make money, and both circumstances can lead to issues with food safety and quality. Food safety refers to the technique of preventing accidental contamination of the food supply. However, food defence is the practice of protecting the food

supply from adulteration with evil intent. Food defence protects against all types of hostile attacks intended to harm food, drink, and their supply systems. The terms food fraud, food defence, food safety, and food quality are frequently used concurrently. The (Global Food Safety Initiative (GFSI), (2014), considered the interactions between food defence, food fraud, food quality, and food safety in its position paper on lowering the risk of food fraud to public health. This strategy physically depicts the relationship between food defence, food fraud, food quality, and food safety rather than having a clear division between them (Figure 1). Contrary to (The World Health Organization (WHO), (2003) and the Food Safety and Inspection Service (FSIS) (2014), the overlapped representation is present.

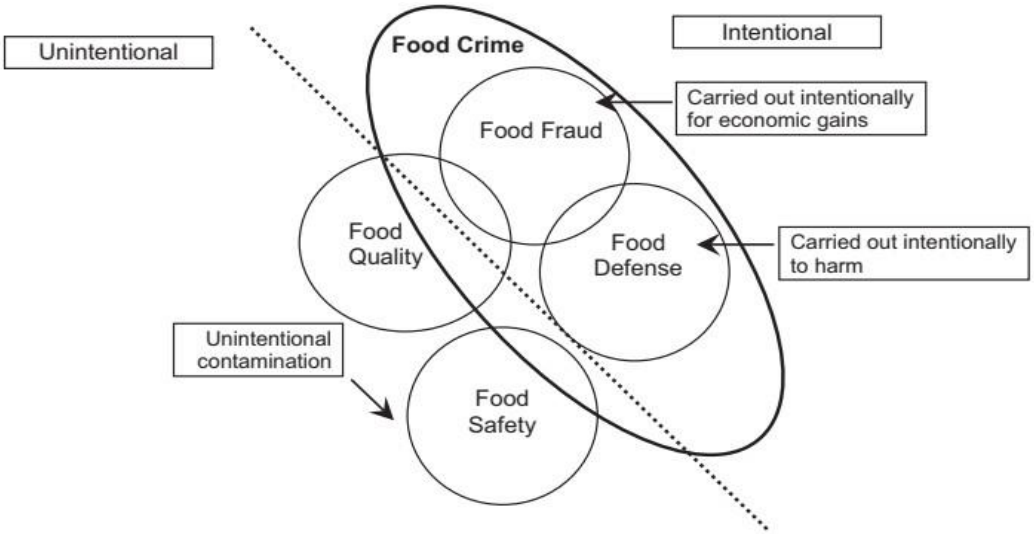

Figure 1: Food alteration, both deliberate and accidental, that requires attention in a food control system

The World Health Organization (2003), emphasised on the importance of distinguishing between food quality and safety, with consequences for both public policy and the improvement of organisational supervision structures. This expression distinction can be applied to the organisational advancement of food defence, food fraud, food quality, and

food safety policies and establish their rationale in terms of what areas they aim to regulate. These 4 components (food defence, food fraud, food quality, and food safety) were also noted by Spink & Moyer (2011) as dissimilar where there was no Economic Motivation Adulteration (EMA) overlap between food quality and food safety (Table 1).

Table 1: The food protection risk matrix (adapted from Spink and Moyer)

Motivation	Intentional	Unintentional
Harm	Food defense	Food safety
Profit	Food fraud	Food quality

Types of food fraud

Food fraud has been classified into the following types:

Dilution – The act of mixing a food product of a high value with an ingredient of a low value.

Substitution – The act of replacing a portion of a food with another of lower value.

Concealment – The act of masking outdated food from consumers to achieve an economic advantage or other malevolent gains.

Unapproved enhancement – it involves the addition of unknown chemicals to food to boost the quality attributes.

Counterfeit – The process of producing food products without the knowledge of its original producers while maintaining its trademark and brand labelling.

Misleading – The false information provided on labels and packaging materials to deceive customers to make economic gains.

Grey market forgery – The diversion of the original product to a different product.

Food fraud incidents and their ranking

Food fraud has been reported for thousands of years, involving olive oil, tea, wine, spices, and honey. Some of the foods correlated with deception include meat and grains, fruit juices, organic foods, caffeine, and other value-added foods (Johnson, 2014). It is uncertain with certainty how widespread food fraud is in Ghana. It is unclear with certainty how pervasive food fraud is in Ghana or globally. This is because persons who practice EMA seek to go undetected and may not certainly have malicious intent. Since most instances of food fraud do not pose a threat to food safety and frequently go undetected by customers, it is difficult to identify them. Nevertheless, certain instances have led to real or hypothetical hazards to the public's health (Bottemiller, 2011). Food fraud may occur on a far greater scale than is currently understood, with documented incidences representing just a small fraction of real incidents. The establishment of databases and repositories is being used to collect and store recent and historical information on economically motivated adulteration (EMA) incidents. The information in these catalogues is the finest now accessible and gives a first step toward understanding the breadth and size of EMA as a way to further notice, battle, and thwart forthcoming theft, although it is not comprehensive and may have certain limitations.

The United States Pharmacopeia Convention (USP) EMA Archives and the National Centre for Food Protection and Defence (NCFPD) EMA Case Record both contain information on the ranking of food fraud (Johnson, 2014). Both databases cover a wide range of topics and frequently depict

EMA in diets and its additives sold around the world. These chronicles undoubtedly do not contain all instances of EMA, occurrences that might take place in non-commercial settings or small-scale markets, or incidents that might be covered by different non-English-speaking news sources.

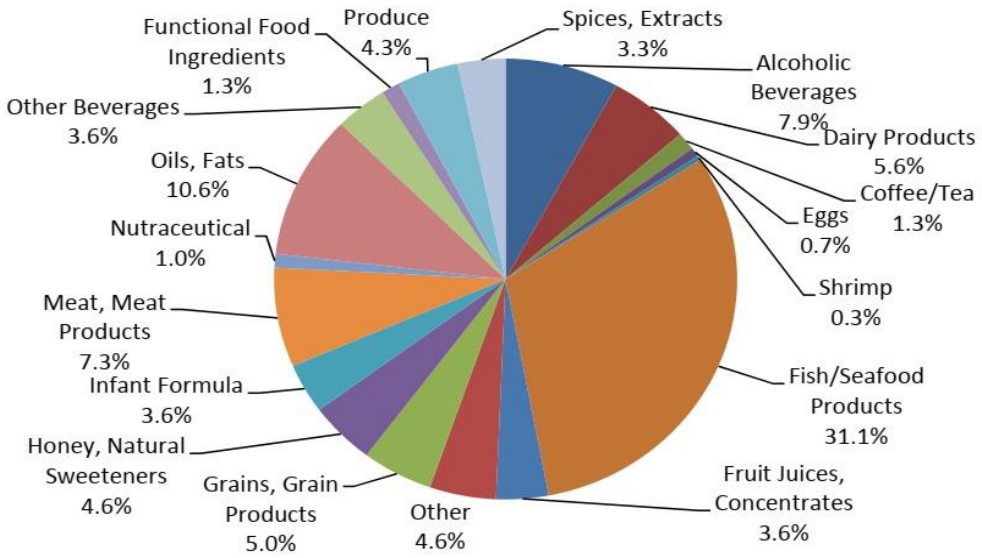

Figure 2: Leading economically motivated adulteration (EMA) incidents by food.
Source: NCFPD CRS from records in the NCFPD EMA case Archives (2013) and based on reported cases.

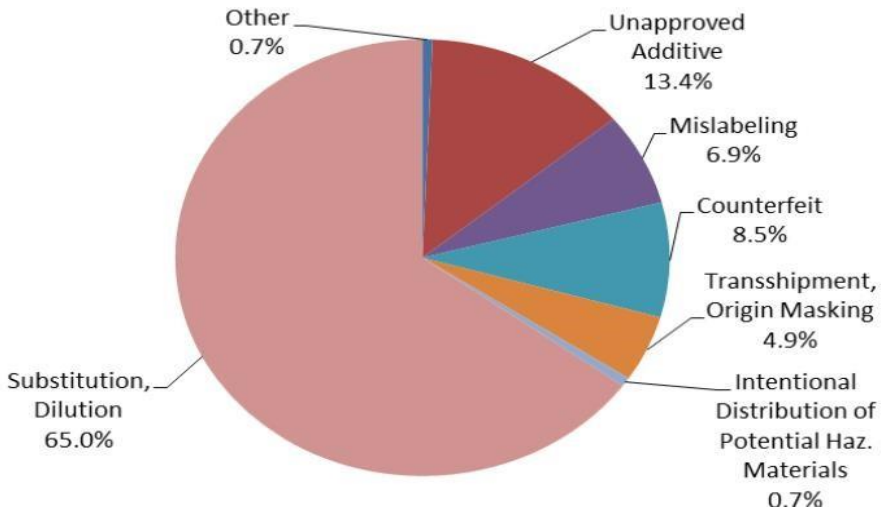

Figure 3: EMA cases by type of adulteration (1980 - 2013).
Source: NCFPD EMA Incident Archive (2014) based on reported cases.

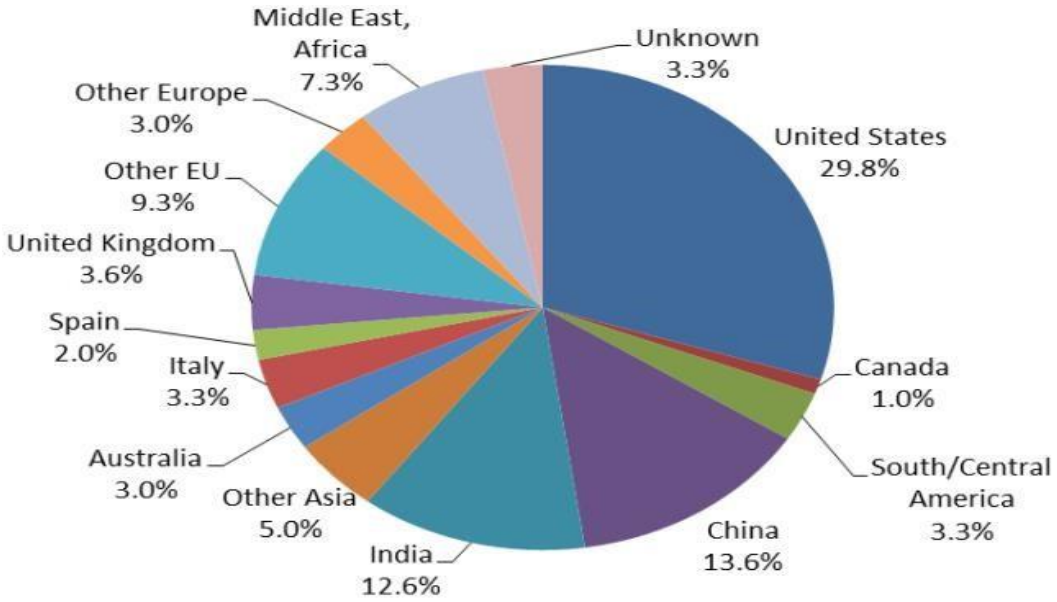

Figure 4: EMA incidents by location produced (1980 – 2013)
Source: CRS from records in the NCFPD EMA case Archive (2013) and based on reported cases.

Food adulteration and its impact on safety

Food adulteration is the introduction of inferior substances to food products to reduce their quality and for economic gain. Adulteration of food began way back but was not noticed due to low population size and less modernization. Today, adulteration has become a common spectacle with the main motive being economic gain. Aside from the monetary aspect, Ayza and Yilma, (2014) cited fraudulence and lack of unintentional quality assessment of products as some of the tools that entice producers, processors and retailers to adulterate food. Nevertheless, the following are reasons outlined by Narayan (2014), for the adulteration of drinks and food; The greediness to increase profit margin, consumers may not be able to afford the original food product, little knowledge about consuming adulterated food products and their associated health problems, when the demand exceeds the supply in the market, and lowering the prices to compete with other producers in the market.

The impact of food adulteration on both consumers and producers

Some food products may be unsafe and dirty to use in everyday life as a result of adulteration and improper handling. Consuming contaminated food has major health effects ranging from ulcers, cancer, diarrhoea, stomach distress, allergies, and brain damage (Bansal et al., 2017; Islam et al., 2018). Nevertheless, the influence of food adulteration does not only rest on the consumer but also on the producers/farmers, manufacturers or processors and the government. When there is a suspicion of adulteration or fraud in a corporation or enterprise, the consumer loses confidence and faith in it. Regulators may recall or destroy tainted products, increase insurance premiums, and incur other expenditures associated with equipment replacement. Regulators may prohibit the production of the alleged contaminated product or the company may be forced to close. In this situation, a company or distributor that relies on the banned product will face financial implications, including lost sales due to a lack of public trust. Spillover may also set in as food adulteration in one country can negatively affect consumers in other countries (Choudhary et al., 2020).

The most affected in times of food fraud outbursts is the consumer. Associated adverse health effects from consuming an adulterated food item may include dropsy, vomiting, oedema, liver disorders, nausea, gastrointestinal problems, respiratory agony and stomach ailment as reported by numerous researchers (Anita & Neetu, 2013; Bansal et al., 2017; Faraz et al., 2013; Lakshmi & Pradesh, 2012). Adulterating rapeseed oil with tricresyl phosphate and mustard oil with argemone has resulted in reports of paralysis and dropsy (Choudhary et al., 2020). These adverse health conditions are the

results of the kind of adulterants used. Calcium carbide, Sudan dye, oxytocin, metallic lead and different types of unauthorized pesticides and herbicide usage can have serious implications. However, the immediate health outcomes of consuming adulterated foods are many, long-term effects such as peptic ulcer, heart disease, kidney damage and abnormalities in the bone marrow have been observed (Bansal et al., 2017).

An alternative subject of concern is mycotoxin contamination, which poses a risk to the safety of food in underdeveloped countries (Wu & Khlangwiset, 2010). Mycotoxins pose a severe menace to the safety of food in countless under-developed countries since fungi are capable of contaminating foods, such as grains and processed spices. They also hamper market growth. Although mycotoxin contamination in developing nations has been extensively researched, nothing has been done to address customer demand for mycotoxin-free food products. Mycotoxins have serious negative consequences for both health and the economy; hence it is vital to monitor consumer awareness and demand for risk reduction.

Food Safety Initiatives in Food Products

Food fraud, product adulteration and counterfeiting are everyday practices in the worldwide food marketplace. Even though there are food laws, they should be enforced to penalize victims who indulge in these acts. Moreover, under-developed countries like Ghana must devise quick inspections of food products for fraud because analytical methods to identify contamination also present certain challenges.

Countries count on laboratory investigations to scrutinize the safety of food products and whether they meet the mandatory standards for

consumption. It is now more important than ever for the food industry to develop and enhance novel approaches to determine food quality. Techniques used in analysing food products for authenticity are summarized in Table 2

Table 2*:* Techniques used in determining the presence of adulterants in food items

Food item	Adulterant	Methods of adulterant detection			Reference
		Physical	Biochemical	Molecular	
Black pepper	Papaya seeds	Due to their shrunken, oval shape, and greenish-brown or brownish-black colouring, papaya seeds can be distinguished from pepper seeds.	Near-infrared spectral imaging (NIR HIS) Midinfrared spectroscopy (MIR)	SCAR	(Dhanya et al., 2009).
Mustard seed and oil	Argemone seeds or oil, rapeseed, ragi	In contrast to argemone seeds, which are black and have a rough, grainy surface that makes it simple to distinguish them under close inspection, mustard seeds have a smooth surface. Moreover, an argemone seed is white when crushed inside, but a mustard seed is yellow.	TLC, HP-TLC	Real time-PCR	(Shelar et al., 2011). (Mustorp et al., 2008).
Turmeric powder	Coloured sawdust, Metanil yellow	When turmeric powder is added to a test tube with a few drops of concentrated HCl, a pink colour will immediately arise and vanish after being diluted with water, indicating the presence of turmeric. Metanil yellow is present if the colour lasts.	TLC, HPLC	RAPD	(Sasikumar et al., 2004).

Food item	Adulterant	Methods of adulterant detection			Reference
		Physical	Biochemical	Molecular	
Coffee	Chicory	Put some coffee powder in a glass of water and stir it around. Chicory sinks, whereas coffee floats. Because there is a lot of caramel, the chicory powder that falls leaves behind coloured trails.	MIR spectroscopy	Real time PCR	(Tornincasa et al., 2010)
Tea	Iron flakes, cashew husk, leather flakes	Distribute a small quantity of the tea sample on some paper, and then cover it with a magnet. The magnet will attract iron flakes. Set a paper ball on fire after making it. Put a small amount of the sample there. The smell of burnt leather is released when leather flakes are present.	GC-MS	Species-specific PCR ITS of 5S rRNA	(Dhiman & Singh, 2003)
Olive oil	Low quality oil	Detection of origin and authenticity verification of virgin olive oil	MIR spectroscopy	SCAR AFLP/RAPD	(Pafundo et al., 2007)
Milk	Water, urea, iron, zinc	Neither glucose nor inverted sugar ELISA, Fourier are present in milk. If the urease transform infrared strip test for glucose is positive, the spectroscopy and substance have been contaminated. Multivariate analysis, Pulsed-field gel electrophoresis, MIR and NIR		PCR-based method, ribotyping, Real-time PCR	(Hurley et al., 2004)

Source: Adapted from (Choudhary et al., 2020).

Yet, the majority of emerging economies are projected to witness a sharp increase in the demand for safer food over the course of the next few decades due to socioeconomic variables like rising incomes, improved levels of education, and increased urbanization (Unnevehr & Hirschhorn, 2000). As a result, consumers, producers, and decision-makers will give food safety concerns more consideration. Additionally, non-destructive methods such as the NIR should be adapted to assist in the detection of adulterants in food that may cause adverse health effects to consumers in developing countries for fast-track detection of fraud.

Application of NIR Spectroscopy and Chemometrics in the Detection of Adulteration

Numerous specialized books (Burns & Ciurczak, 2007; Williams & Norris, 1987), thousands of near-infrared spectroscopy (NIRS) papers from the past three decades, and the proceedings of the 19th International NIRS conferences held by the International Council of Near Infrared Spectroscopy (Pérez-Marín et al., 2004), attest to the (NIRS) performance's suitability for measuring both quantitative and qualitative sample properties. Despite the fact that maintaining an outstanding record for accuracy and reproducibility among those in the food sectors, pharmaceutical and chemical industries, NIRS applications have outpaced all other techniques in terms of diversity. NIRS has been used to examine the authenticity of a wide range of foods, including rice, meat, fish, honey, dairy milk, coffee, oils, spices, tea, onion powder, mushrooms, rice, juice, whisky, and wine (Downey, 2016). Numerous researchers have conducted research utilizing at-line laboratory tools which can be categorized as viability studies. For instance, in portable, or handheld

applications, NIR technology is ideally suited. NIRS are perfect for use outside of the lab for food control at multiple crucial locations throughout the food chain because of their simplicity, speed, selectivity, and ability to function without sample pre-treatment.

A new generation of lightweight, portable NIRS equipment has recently been created that is perfect for on-site measurements (Figure 2).

Figure 5: Images of handheld or portable NIR devices.
Source: (Dos Santos et al., 2013; Pu et al., 2021; Zhu et al., 2022).

Nevertheless, the mainstream of these miniature sensors has not been industrialized for use in the food industry, where the complex nature of the food matrix is a hurdle (Crocombe, 2018; Yan & Siesler, 2018). Pérez-Marín & Garrido-Varo (2006), reported that it is only recently that researchers have seen their potential for application in real-world food business situations; nonetheless, specific adaptations and changes must be made before the food sector can make use of them. However, sequential studies have revealed that it

can be used in actual food systems and that it is extensively used in the food industry with several studies of in situ NIR application.

Its wavelength ranges from 800 to 2500 nm and an absorption range of 800 to 1800 nm corresponds to overtone molecular absorptions (Czarnecki et al., 2015). The C-H, O-H, and N-H functional groups of the samples being measured are mostly connected with the combination bands of fundamental vibrational transitions in the 1800–2500 nm wavelength range. When samples are scanned with NIRS, bands, lines or peaks are produced as a result of the intricate anharmonicity vibrational motion of the chemical bonds in the samples (Rodriguez-Saona & Allendorf, 2011; Shenk & Westerhaus, 1994). When used in conjunction with chemometric techniques, NIRS has developed into a potent tool for the qualitative and quantitative analysis of food constituents (Bevilacqua et al., 2013; González Martín et al., 2014; Teye et al., 2020).

Chemometrics

Cen & He (2007), reported that chemometrics analyses of the chemical data of a sample to produce the most relevant chemical information is possible using mathematical, statistical, and other methods based on formal logic. Principal component analysis (PCA) is one of the exploratory techniques used in chemometric data analysis. This helps condense the data into a smaller number of easily understood variables and lowers the dimension of the data matrix generated by NIRS. Principal components (PCs) are these variables, and by forming clusters, they offer useful information about the commonalities between the samples (Teye et al., 2014).

The first and second derivatives are mathematical pre-treatments used to evaluate the spectral signal produced from scanned samples. The spectral signal's random noise and baseline drift are both eliminated by this approach. With the help of chemometrics and NIRS, it has been possible to successfully detect adulteration in peanut butter which was tampered with cassava flour (Bimpong et al., 2023).

Despite the existence of further identification methods including the iodide test, microscopic analysis, and sensory recognition, each has its limitations. The iodide test is mostly used to determine whether samples contain any starchy components (Li, 2008). Microscopic identification is usually a challenging process that requires sample pre-treatment. On the other hand, sensory recognition is difficult to quantify and depends on experience. It is employed to differentiate between the colour, flavour, and aroma of samples. Given this context, NIR spectroscopy is a critical tool for the prompt and efficient detection of food product fraud.

CHAPTER THREE

METHODOLOGY

Introduction

This current study seeks to investigate the safety and quality of groundnut paste in the Central region of Ghana using near-infrared spectroscopy coupled with a smartphone. This chapter presents the experimental design used in studying the safety and quality of groundnut paste adulteration in Ghana using near-infrared spectroscopy. It presents the materials and method, preparation of groundnut paste, determination of the physicochemical properties (moisture content, protein, fat/oil, acid value, peroxide value, free fatty acid, colour, chroma, browning index), safety (yeast and moulds) of groundnut paste and detection of adulterants in groundnut paste.

Study Area

Groundnut paste samples were collected from five major markets in the Central region of Ghana namely Kotokuraba, Twifo Praso, Mankessim, Swedru and Kasoa market. The samples collected were put in a plastic jar sealed and labelled. A control sample of the groundnut paste was prepared at Fountain Foods factory. Cassava flour and roasted maize flour were used as adulterants to dilute the groundnut paste samples that were prepared at Fountains Foods Factory. An extreme vertices design was used in generating the proportion of the prepared groundnut paste to that of the adulterants in percentages;10%, 20%, 30%, 40% and 50%. Samples were transported to the Technology Village laboratory of the School of Agriculture, University of Cape Coast, Cape Coast, Ghana, for further laboratory investigations.

Preparation of groundnut paste samples

The preparation of groundnut paste took place at Fountain Foods processing factory, where shelled groundnuts were graded base on sizes and cleaned to separate high-quality kernels. The nuts were then roasted at 130^{o}C for 20 minutes using a commercial oven. The roasted groundnut skins were removed using a groundnut peeling machine before processing into a paste.

Table 3: Sampling of commercial groundnut paste from various markets

Name of Market	Location	Number of samples
Mankessim	Mankessim	10
Swedru	Swedru	10
Kasoa	Kasoa	10
Twifo Praso	Twifo Praso	10
Kotokoraba	Kotokoraba	10

Experimental design

Mixture design was used in generating the proportions of pure groundnut paste to the adulterants for the study using Minitab 17 statistical software (2010). The constraint of component proportion for the groundnut paste samples is shown in Table 4. The study design followed the extreme vertices design since the design is not an L-simplex. The design was augmented at the centre and axial points.

Table 4: Mixture design for groundnut paste adulteration using cassava flour and roasted maize flour as an adulterant.

Sample	Lower limit %	Upper limit %
Groundnut paste	70	100
Cassava flour	0	30
Roasted maize flour	0	30

Adulteration of samples

The groundnut paste and the adulterants were weighed on an electronic balance (model Ohaus, PA4101, USA) as generated by the mixture design. The groundnut paste sample was then spiked with the adulterants. Each combination was stirred using a stirrer to ensure a uniform mixture. Approximately 10g of each mixture was weighed into a plastic jar sealed, labelled and stored in a dry place for the NIR spectroscopy analysis. A total of 320 samples were used in this study.

Table 5: Combinations of groundnut paste and its adulterants, a reference of the mixture sample produced for the NIRS experimental set

Std Order	Groundnut paste samples	Adulterants (Cassava flour or roasted maize flour)	Nature of sample	Number of samples
1	10.0	0	Pure	20
2	9.5	0.5	Adulterated	20
3	9.0	1.0	Adulterated	20
4	8.5	1.5	Adulterated	20
5	8.0	2.0	Adulterated	20
6	7.5	2.5	Adulterated	20
7	7.0	3.0	Adulterated	20
8	0	10	Adulterant	20

Physicochemical Analysis

The physicochemical analysis conducted on the groundnut paste samples are as follows; moisture content, protein content, fats and oil, free fatty acids, Acid value and Peroxide value.

Moisture content

The moisture content of the peanut butter samples was determined by the method used by Leffler et al (2008). Porcelain crucibles were washed dried and weighed. 10g of groundnut paste samples were put into clean oven-dried crucibles and weighed. The crucibles containing the sample were spread over the base of the oven to ensure equal distribution of heat. Groundnut paste samples were kept in a thermostatically controlled oven at 105^{o}C for 48 hours. After 48 hours of oven drying, samples were removed and cooled in a desiccator and weighed. Experiment was conducted in triplicate. The moisture content was calculated as the percentage loss of weight by the sample using the formula below.

Calculations

$$Moisture\ content\ (\%) = \frac{\text{Wet Weight (w1)} - \text{Dry Weight (w2)}}{\text{Wet Weight (w1)}} \times 100 \quad (1)$$

Where w_1 = initial weight of the sample (g)

w_2 = final weight of the sample (g)

Protein Content Determination

The Kjeldahl method was used to determine the protein content in groundnut paste samples. This method is divided into 3 procedures: digestion, distillation and titration.

Digestion

0.2g of groundnut paste sample will be weighed into a 100 ml Kjeldahl flask. 4.4ml of the digestion reagent will be added to the peanut butter samples digested at a temperature of 360^{o}C for 2 hours. After the digestion of the groundnut paste samples, the digests were transferred into 100ml volumetric flasks to make up for the volume.

Distillation

A steam distillation apparatus was set up. The distillation apparatus was flushed with distilled water for about 20 minutes. After cleaning the apparatus, 5 ml of boric acid solution was poured into a 100 ml conical flask which was placed under the condenser of the distillation apparatus with the tip of the condenser completely immersed in the boric acid solution. An aliquot of the sample digested was also transferred into the reaction chamber through a trap funnel. 10ml of an alkali mixture was added to commence distillation immediately.

Titration

The distillate was titrated with 0.1N HCl solution until the solution changed from green to wine red which is the initial colour of the indicator. Digestion blank was also treated the same way and was been subtracted from the sample titre value. The titre values obtained were used to calculate the nitrogen and hence the protein content. The conversion factor which was used is 6.25.

$$\%\ Total\ Nitrogen = \frac{(Sample\ titre\ value - Blank\ titre\ value) \times 0.1 \times 0.01401 \times 100}{Sample\ weight \times 10} \quad (2)$$

%Protein = %N x 6.25.

Oil/ Fat Determination

Procedure

10 g of the milled groundnut paste samples were weighed into a 50 ×10 mm soxhlet extraction thimble. This was transferred to a 50 ml capacity soxhlet extractor. A clean dry 250 ml round bottom flask was weighed. 150 ml Petroleum ether at a boiling point of 60^{o}C was added and connected to the soxhlet extractor and extraction was done for 6 hours using a heating mantle as a source of heating. After 6 hours, the flask was removed and placed in an oven at 60^{o}C for 2 hours. The round bottom flask was removed, cooled in a desiccator and weighed. The percentage of fat/oil was calculated as follows.

Calculation

$$\text{Crude Fat (\%)} = \frac{W\,(g) \times 100}{\text{Sample}\ (g)}, \qquad (3)$$

Where W is the Weight of Oil

Peroxide Value Determination

A 250 ml conical flask was filled with 5 g of the oil. The flask was filled with 30 ml of a mixture of acetic acid and chloroform, and the mixture was allowed to settle for a minute, with periodic spinning of the flasks. Then, 30 ml of purified water was added. After titrating the mixture with 0.1N sodium thiosulphate until a brown hue was achieved, 0.5ml of 1% starch solution was added, and titration was carried out again until the blue/grey colour disappeared. During the titration process, the mixture was agitated vigorously to release all of the iodine from the chloroform layer (Roiaini et al., 2015).

Acid Value

The acid value of an oil/fat is the number of potassium hydroxides required to neutralize the free acids resulting from the complete hydrolysis of 1g of the sample. A 10 g of the groundnut paste was dispensed into a thimble and the oil extracted with petroleum ether for 8 h in a soxhlet apparatus. Then evaporation of the solvent was completely done under reduced pressure in a rotary evaporator. The oil obtained in the extraction flask was dissolved with warm neutral alcohol solution and titrated with standard 0.1M of sodium hydroxide solution to a faint pink colour which persists for 10s. The acid value was determined using the equation below:

$$\% \text{ Acid Value (as oleic acid)} = \frac{(56.1 \text{ x VM})}{m} \text{x } 100 \qquad (4)$$

V = volume in ml of standard sodium hydroxide solution used (Titre value).

M = molarity of standard sodium hydroxide solution

m = mass in g of the sample taken for the test.

56.1g/mol = Molecular Weight of KOH

Free fatty Acid Determination

A 250 ml conical flask was filled with 5g of the oil. Next, 50 ml of 99% isopropanol was used to dissolve the sample, and everything was thoroughly mixed. thereafter the mixture was titrated using a solution of 0.1N sodium hydroxide using phenolphthalein as an indicator. The indication changes to pink for a minimum of 30 seconds to indicate the achievement of the final drop (Roiaini et al., 2015).

Colour Analysis Determination

Colour analysis was performed using a Hunter lab colourimeter, and L*, a*, and b* values were recorded. The L* value describes a colour's brightness on a scale of 0 to 100, with zero being the darkest colour (or darkness) and 100 representing the lightest (or whitest) colour. The * values are represented by a red-to-green colour scale, with red/brown indicating positive values and green representing negative ones. The b* values are represented by a colour spectrum ranging from blue to yellow, with yellow indicating positive values and blue representing negative values. Browning index (BI) is a crucial measure for both enzymatic and non-enzymatic browning processes, indicating the purity of the brown colour. The chroma and BI were estimated using the calculations recommended by Wrolstad and Smith(2017).

Chroma = $\sqrt{(a^{*2} + b^{*2})}$ (5)

BI = $\frac{100 \times (x - 0.31)}{0.17}$ (6)

x = $\frac{a^* + 1.75\ L^*}{5.645\ L^* + a^* - 3.012b^*}$ (7)

Fungal plating, enumeration and identification

The enumeration of total fungi was performed in duplicates, using 10 g samples diluted in 90 mL of phosphate-buffered saline (PBS). Samples were homogenized for 60 s, corresponding to a dilution of 10^{-1}. From this, dilutions 10^{-2}, 10^{-3}, 10^{-4}, and 10^{-5} were made up using tubes containing 9 mL of PBS. Surface plating was carried out on potato dextrose agar (PDA), with 100 µL inoculum. Plates were incubated upright at 25 ºC for 5 days. After incubation,

total colonies were counted, and the results were expressed in CFU/g of groundnut paste. Colonies of filamentous fungi were transferred to Malt Extract Agar (MEA) and incubated again at 25 ºC for 5 days. Afterwards, the colonies were identified at the genus level, based on their morphological, macroscopic, and microscopic characteristics as described by Samson (2010). To achieve these, a stereoscope microscope (Olympus SXZ16, Olympus, USA) and an optical microscope (ZEISS Stemi 2000-C, Germany) were used. To observe the precise arrangement of the conidiophores and accurately identify them, genera were also prepared on slide cultures using Riddel's simple agar block method (Samson et al., 2010).

Spectral Acquisition

A handheld NIR spectrometer (InnoSpectra model NIR-S-G1) was used to scan the pure and adulterated groundnut paste samples. A wavelength in the range of 900 to 1700 nm at 1 nm resolution, was used to attain the spectral data. The NIR spectrometer was operated using a smartphone application with spectral data stored remotely. Each sample was scanned three times and at each scan, the samples were rotated to collect more representative spectra of the whole sample. Spectra measured using the InnoSpectra device (handheld NIR spectrometer) were stored in the cloud and retrieved for analysis.

Multivariate Analysis

Principal Component Analysis

All computation and chemometric analyses were done with MATLAB (Math Works, Inc., USA, version 9.6.0). All codes were in-house and written with MATLAB. The reflectance spectra obtained were transformed into

absorbance spectra. This was done to compare the performance of the different spectral profiles to determine the adulteration concentration in the groundnut paste samples. Several pre-processing techniques (such as multiplicative scatter correction [MSC], first derivative [FD], second derivative [SD], mean centring [MC] and standard normal variant [SNV]) were evaluated using MATLAB software for the selection of algorithms. PCA, an unsupervised procedure, was applied to explore the differences between the pure groundnut paste and adulterated samples. This was done to reduce the size of the data matrix by compressing the data into a few new variables known as principal components (PCs). The PCs (PC1 and PC2) provide and explain useful information regarding the data (Teye et al., 2015).

Data Partitioning

The spectral data set for pure groundnut paste (20), adulterated samples (240), pure cassava flour (20) and pure roasted maize flour (20) were downloaded individually, and two sets (the training set and the test set) of each category were created. A total of 90 samples were chosen as the testing set when the model was being tested, and 210 samples were chosen as the training set when the model was being built. This was done to prevent bias in the division.

Data Analysis

The experimental results for the chemical analysis were expressed as the mean ± standard deviation (SD) of triplicates. The data were subjected to one-way analysis of variance (ANOVA), and Fisher's least significant difference (LSD) tests using Minitab 16 software were carried out to ascertain significant effects at $p < 0.05$ level of significance among treatments.

CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

This chapter presents the results and discussion on the safety and quality of groundnut paste adulteration in Ghana using near-infrared spectroscopy. It presents the results and discussion on the determination of the physicochemical properties (moisture content, protein, fat/oil, acid value, peroxide value, free fatty acid, colour, chroma, browning index,) safety (yeast and moulds) and detection of adulterants in groundnut paste.

Quality parameters of commercial groundnut paste.

The results of the quality parameters of commercial groundnut paste were presented in Tables 6, 7 and 8. The percentage moisture content of commercial groundnut paste samples obtained from the five (5) major markets in the Central region ranges from 0.06 to 6.683% (Table 6). Samples from Kotokuraba, Twifo Praso, Swedru, Mankessim and Kasoa markets were average (1.57% to 3.07%) which falls within the Codex Alimentarius standard for the moisture content of groundnut paste (Codex, 2015).

Samples of commercial groundnut paste from the Swedru market showed a higher protein content of 24.48% followed by the control sample (23.53%). Samples from the Twifo Praso market and Kotokuraba market recorded the lowest protein content and were significantly different from each other. All the groundnut paste samples from various major markets in the central region did not meet the minimum requirement of the Codex Alimentarius standard and Ghana Standard Authority for protein content (GS 955:2019) as shown in Table 6.

The percentage of fat and oil content in commercial groundnut paste samples obtained from the 5 major markets in the Central region ranges from 23.49%-38.13%. (Table 6). The control sample has an average fat/oil content of 38.02% which falls below the threshold of the Codex standard for fats and oil. Samples from other markets range from (31.58%-23.49%) which falls below the threshold for Codex Alimentarius Standard for fats/oil content as shown in Table 6.

The evaluation of acid value levels in the commercial groundnut paste samples obtained from the control and Twifo Praso markets revealed that the Acid values were within the Codex Standard range. The acid values of the samples range from 3.709 to 6.181 (Table 6). Samples from Mankessim, Kotokuraba, Swedru and Kasoa recorded the highest acid values of 4.41%, 6.15%, 4.26% and 5.04%, respectively.

The evaluation of Acid value levels in the commercial groundnut paste samples obtained from the control and Twifo Praso markets revealed that the Acid values were within the Codex Standard range. The acid values of the samples range from 3.709 to 6.181 (Table 6).

The evaluation of peroxide value levels in groundnut paste samples obtained from various markets revealed that the peroxide values were within the peroxide value range as recommended by the Codex Alimentarius Commission. The peroxide values of the samples range from 2.515 to 3.114 (Table 6). Samples from Kotokuraba market recorded the highest peroxide value (5.35) and this was statistically different from samples collected from the other major markets.

Table 6 shows the result of free fatty acids (FFA) of groundnut paste oil samples collected from the various major markets in the Central region of Ghana. From the table it was observed there were variations among the means of FFA in the samples collected from the various markets assessed, with means of 3.09%, 2.21%, 1.91%, 2.14% and 2.53% This variability was also observed in samples collected in the various markets. There was a statistical difference of $p < 0.05$ in samples from Kotokuraba, Twifo Praso and Kasoa. However, there was no statistical difference ($p<0.05$) between samples from Mankessim and Swedru.

Table 6: Quality parameters of commercial groundnut paste

Market	Moisture%	Protein%	Fat/Oil %	Acid Value %	P V meq	FFA
Kotokuraba	1.57±1.17^{a}	22.30 ± 0.06^{c}	23.52 ± 0.04^{e}	6.15 ± 0.04^{a}	5.35 ± 0.39^{a}	3.09 ± 0.02^{a}
Mankessim	3.07±0.15^{a}	22.58 ± 0.08^{b}	31.58 ± 0.48^{bc}	4.41 ± 0.01^{c}	3.78 ± 0.01^{c}	2.21 ± 0.00^{c}
Twifo Praso	1.83±0.85^{a}	21.37 ± 0.07^{d}	25.07 ± 0.04^{d}	3.80 ± 0.13^{d}	2.95 ± 0.09^{b}	1.91 ± 0.07^{d}
Swedru	1.17±0.49^{a}	24.48 ± 0.23^{a}	24.86 ± 0.18^{d}	4.26 ± 0.07^{c}	2.89 ± 0.30^{e}	2.14 ± 0.04^{c}
Kasoa	2.03±0.67^{a}	22.67 ± 0.09^{a}	24.87 ± 0.9^{d}	5.04 ± 0.01^{b}	3.30 ± 0.06^{d}	2.53 ± 0.00^{b}
Codex	3.20	25.0	45.0	4.0	10.0	5.0

Means in the same column which do not share the same letter are significantly different ($p<0.05$).

Moisture content of commercial groundnut paste

The result of moisture content determination of commercial groundnut paste reveals that the sample from Mankessim (3.07%) has high moisture content compared to groundnut paste samples from Kotokuraba (1.57%), Twifo Praso (1.83%), Swedru (1.17%) and Kasoa (2.03%) as displayed on table 6. Moisture content has been identified as a major factor that determines the life expectancy of food products. However, moisture content can influence the organoleptic properties of food such as taste and appearance. It gives an idea of whether a product may have a longer or shorter life span notwithstanding the properties of the food product whether in a dry or wet state (Joardder et al., 2019). From Table 6, the sample from the Swedru market recorded a low moisture content of (1.17%) which is not statistically different from the codex standard.

A study conducted by Boli et al. (2017) from Côte d'Ivoire showed a moisture content of 1.23 to 4.50% which is in agreement with the result obtained from this study. According to Guy-Rolande et al. (2024), groundnut paste should have 1.65-3.53% moisture content per 10g per sample. The groundnut paste sample from various markets falls within the range except for the control sample which falls outside the range. Reducing moisture content in groundnut paste is vital to prevent mould growth. Also, after harvest, peanuts should have an appropriate aeration to prevent the development of microflora and a decline in quality (Dorley, 2015).

The commercial groundnut paste from the Swedru market may be of good quality and have a longer shelf life followed by Kotokuraba, Twifo Praso, Kasoa and Mankessim respectively due to their moisture content

presented in this study. The presence of high moisture content in groundnut paste can predispose it to insect and worm infestation, thereby resulting in the loss of its quality and nutritional composition. The physical, chemical and sensory properties of groundnut pastes are affected by the changes in moisture content since water provides a suitable condition for chemical reactions to take place. An increase in moisture content in food makes it susceptible for microbes to thrive in its environment (Joardder et al., 2019).

It is therefore imperative to conduct periodic assessments to evaluate the moisture content in foods. The optimum packaging materials for extending food shelf life can be chosen from this information. Groundnut paste purchased from the markets for this study is mostly in transparent airtight containers for sale. Groundnut paste can absorb water from its environment if it is not properly packaged and the increase in moisture content is known to accelerate mould growth (Tripathi & Mishra, 2011).

Protein content of commercial groundnut paste.

The result obtained from protein content determination revealed that the groundnut paste sample from the Swedru market (24.48%) is equivalent to the minimum requirement of the Codex standard (25.0). However, samples from the Kasoa market (22.67%), Mankessim market (22.58%), Kotokuraba market (22.30%) and Twifo Praso (21.37%), fall outside the range of the Codex standard and are different from the Codex standard as recorded in the Table 6.

Groundnut paste is considered a valuable source of protein in improving the nutritional status of humans (Boli et al., 2017). Protein plays a critical role in human development such as muscle growth and repair of worn-

out tissues. Nevertheless, an insufficient intake of protein in a diet as recommended by the Codex standard may result in “Kwashiorkor”. In Table 6 The protein content in groundnut paste samples collected from the Swedru market is 24.48% and this result is in agreement with the findings of Boli et al. (2017) from Côte d’Ivoire which indicated that protein content of (23.33 to 28.58%). However, groundnut paste samples from the Mankessim market, Kotokuraba market and Twifo Praso are statistically different ($p>0.05$) from the results obtained by Boli et al. (2017) and Codex standard which could be a result of the introduction of stabilizers, flavours and adulterants into the groundnut paste along the groundnut paste value chain (Shibli et al., 2019).

Fat/oil content of commercial groundnut paste

All the market samples (Kotokuraba, Mankessim, Twifo Praso, Swedru, and Kasoa) have fat/oil contents significantly lower than the Codex standard of 45.0%. The highest fat/oil content observed in Mankessim (31.58%) is still approximately 13.42 percentage points lower than the Codex standard. This substantial difference indicates that the peanut paste from these markets does not meet the Codex standard for fat/oil content.

The lower fat/oil content in the peanut paste from these markets means they provide fewer calories from fats compared to the Codex standard, which might be desirable for consumers seeking lower-fat products but may not meet the needs of those looking for high-energy food sources. This significant deviation from the Codex standard suggests variations in peanut quality, processing methods, or both, such as processing techniques and handling practices contributing to the lower fat/oil content observed (Mahfoud et al., 2023). Consequently, peanut paste products from these markets may be

marketed as lower-fat alternatives appealing to health-conscious consumers; however, they may not compete directly with products adhering to the Codex standard regarding energy density and specific culinary applications that require higher fat content (Alimentarius, 1999).

Acid value for commercial groundnut paste.

An accurate indicator of the percentage of free fatty acids in a specific volume of oil is its acid value. It is a measurement of how much lipase action has broken down the triglycerides in the oil into free fatty acids; the acid value is based on the degree of rancidity, which is used as an index of freshness. (Adebayo et al., 2012). According to the Codex Alimentarius standard, the maximum acid value for oil should be 4.0. From Table 6, groundnut paste from Twifo Praso falls within the Codex Alimentarius standard whereas samples from Kotokuraba, Mankessim, Kasoa and Swedru do not meet the Codex standard requirement and therefore they are susceptible to rancidity.

The values obtained from Mankessim and Swedru agree with those obtained from Essei and Amadi (2009), for butternut oil (2.25 to 4.50) and samples from Kasoa and Kotokuraba also agree with Pearson (1976), who reported acid values of 4 for sesame, soybean, sunflower and rape seed and 7 for olive oil. Nevertheless, it is well known that this parameter indicates a degree of deterioration and therefore can be concluded that processing method, poor storage conditions, microbial activity and quality of raw materials may result in high acidic value and rancidity.

Peroxide value of commercial groundnut paste.

Peroxide value is a vital factor used in evaluating the quality of peanut oil. It is an indicator of lipid oxidation. According to the codex standard, the best peroxide value for plant-based cold press oil is 10meq (Alimentarius, 1999). From Table (6), it was observed from the research findings that the peroxide values obtained from various markets (Kotokuraba, Mankessim, Twifo Praso, Swedru and Kasoa) were within the Codex Alimentarius standard with mean values of 2.89meq, 2.95meq, 3.30meq, 3.78meq and 5.35meq respectively. A statistical difference ($p<0.05$) was observed from the samples obtained from the Kotokuraba market, Mankessim and Kasoa market which has a lower peroxide value and samples from Swedru and Twifo Praso markets did not show any statistical difference ($p<0.05$).

Samples obtained from the five major markets had different peroxide values. These differences could have been caused by air exposure, high processing temperatures, and storage times that allowed for oxidation and spoiling (Ugo et al., 2024). Low peroxide value was documented by Ngando-Ebongue et al. (2012) with values of 2.07, 1.48 – 5.71 and 2.67 MeqO_2/kg) and high peroxide value was noticed in the findings of Okechalu et al. (2011), who reported high peroxide values of 23.2 – 35.5 MeqO_2/kg. This oxidized oil could be very harmful for consumption (Tagoe et al., 2012). In addition to these obvious negative impacts on the oil's sensory qualities, peroxidation also renders the oil hazardous to human health because the free radicals it produces have been shown to cause cancer (Ugo et al., 2024).

Free Fatty Acids (FFA) on Commercial groundnut paste.

FFA is a frequently used measure for determining the quality of peanut oil; higher FFA has been linked to an increased risk of coronary heart disease, a main cause of death in Western countries (Ngando-Ebongue et al., 2012). To reduce enzymatic (lipase) activity and subsequent Free Fatty Acid (FFA) formation, peanuts must be handled carefully and processed quickly after harvest to minimize moisture exposure, which catalyzes hydrolytic rancidity. Additionally, rapid processing helps suppress lipid oxidation caused by reactive oxygen species, preserving oil quality and preventing off-flavors (Ugo et al., 2024). From Table 7, the FFA values of peanut oil ranged from 1.86% to 3.09% which were within the safe level as specified by the Codex Alimentarius Commission (2011). Peanut oil with low FFA is an indication that the oil has been processed from fresh, unbruised peanuts and carefully handled during production, storage, and transportation (Nizam & Mahmud, 2021).

Hence, the increased value of FFA, slightly above normal may be attributed to proper post-handling techniques during the production process and storage period (Nizam & Mahmud, 2021).

Colour classification of groundnut pasteThe colour values of L*, a* and b* of the groundnut paste purchased from the major markets in the Central region are displayed in Table 7. The L* values of the groundnut paste sample in the various markets range from 10.69 to 20.29, a* value ranges from 4.59 to 7.09 and b* values range from 6.12 ≤ 11.79. The markets that recorded the highest L*, a* and b* values are Twifo Praso, Mankessim and Kasoa respectively. Samples from Twifo Praso demonstrated the highest level of

lightness with an L* value of 20.14 and were statistically different $p<0.05$ from samples from Mankessim, Kotokuraba, Swedru and Kasoa. All samples from the various markets showed a level of redness but were not statistically different and all samples (b*) showed some levels of yellowness that were statistically different. The chroma values of the groundnut paste range from 9.02 to 13.18 and are statistically different and browning index values also range from 88.23 to 135.29 and are also statistically different ($p < 0.05$).

Table 7: Quality parameters of commercial groundnut paste from the various major markets in the Central region.

Sample	L*	a*	b*	Chroma	BI
Kotokuraba	10.91 ± 0.31^{c}	6.30 ± 0.81^{a}	6.54 ± 0.60^{c}	9.11 ± 0.13^{b}	126.47 ± 4.16^{a}
Mankessim	17.06 ± 1.25^{b}	5.26 ± 0.89^{a}	10.18 ± 0.27^{a}	11.57 ± 0.18^{a}	108.83 ± 12.48^{b}
Twifo Praso	20.14 ± 0.20^{a}	5.59 ± 0.41^{a}	11.17 ± 0.87^{a}	12.49 ± 0.97^{b}	97.06 ± 4.16^{c}
Swedru	11.21 ± 0.04^{c}	6.75 ± 0.47^{a}	7.01 ± 0.01^{b}	9.74 ± 0.34^{b}	135.3 ± 0.0^{a}
Kasoa	16.20 ± 1.18^{b}	5.32 ± 1.03^{a}	8.22 ± 0.64^{b}	9.795 ± 1.10^{b}	91.18 ± 4.16^{c}

Means in the same column which do not share the same letter are significantly different ($p<0.05$).

Colour can influence consumer impression of a manufactured food product (Tortoe et al. (2017) found that groundnut paste colour has a significant impact on food quality, consumer preferences, and marketability. Groundnut paste loses colour due to carotenoid pigment oxidation. Masih et al. (2017) reported that carotenoid pigment oxidises depending on factors such as moisture content, storage, temperature, environment, and light exposure.

The results of this study showed that Twifo Praso has a higher moisture content followed by Mankessim, Kasoa, Swedru and Kotokuraba respectively. Low moisture content gives a high brightness value while a higher moisture content showed a low brightness value as seen from the colour analysis for all the groundnut paste samples. The brightness value ranges from 10.69 to 20.29 which means that groundnut paste samples from Twifo Praso are dark in colour followed by Mankessim, Kasoa, Swedru and Kotokuraba. The result in low brightness value of the groundnut paste samples could be a result of humidity in the oven, light exposure and improper storage of the groundnut paste. This observation agrees with Masih et al. (2017), who reported that colour change could be due to high moisture content.

Higher a* values are typically associated with more intense roasting which could lead to the Maillard reaction responsible for browning and developing flavours in roasted peanuts and also enhances the brown hues in the final product (Masih et al., 2017). Swedru and Kotokuraba, with higher a* values, likely underwent more intense or prolonged roasting, leading to a richer brown colour. The colour of groundnut paste can significantly affect consumer perception and preference; products with higher a* values might be perceived as more robustly flavoured and well-roasted, appealing to those who

prefer a deeper, roasted flavour profile. Conversely, products with lower a* values, like Mankessim groundnut paste, might be preferred by consumers who favour a milder flavour and lighter roast. Consistency in a* values can be an indicator of quality control in the production process, as manufacturers aiming for a specific colour profile would need to monitor and control the roasting process to achieve the desired a* values consistently. Variations in these values could indicate differences in the roasting process, or other factors affecting the final product (Mubaiwa et al., 2018). This finding is in agreement with Masih et al. (2017), who reported that a higher amount of protein content could result in a Maillard reaction.

The b* values represent the yellow/blue component, ranging from 6.12 to 11.79, with all samples showing positive b* values, indicating the presence of yellow hues. Twifo Praso groundnut paste has the highest b* value (11.17), suggesting a more intense yellow colour, which can be attributed to the specific type of peanuts used or the roasting process, as the Maillard reaction and caramelization during roasting often enhance yellow pigmentation (Adrian, 2019). In contrast, Kotokuraba groundnut paste has the lowest b* value (6.54), indicating a less intense yellow colour, which could result from a different roasting level potentially affecting consumer perception of freshness and quality (Yanti et al., 2018). Consistent b* values are crucial for quality control, as they reflect the product's visual appeal and can influence consumer preference (Sithole et al., 2022).

Chroma is a crucial parameter in food quality assessment, as it affects visual appeal and consumer perception. Studies have shown that higher

chroma values in food products are often associated with higher consumer acceptance and perceived quality (Wrolstad & Smith, 2017).

These chemical reactions not only enhance colour but also contribute to the development of complex flavours. The relationship between chroma and roasting intensity has been well-documented, with more intense roasting leading to higher chroma values due to the Maillard reaction and caramelization (Adrian, 2019). From Table (8) the chroma values for the groundnut paste samples range from 9.02 to 13.18, indicating varying levels of colour intensity and roasting. Twifo Praso groundnut paste, with the highest chroma, suggests the most intense colour and flavour, likely due to a more pronounced roasting process which may have adverse health effects on the consumer because they could be exposed to Maillard reaction products. Mankessim groundnut paste also shows a high chroma, indicating vivid colour and strong flavour. Kotokuraba groundnut paste, with the lowest chroma, suggests a milder roasting process and subdued colour and so may be the safest for consumers.

The Browning Index (BI) quantifies the degree of browning in food products, affecting appearance, flavour, and nutritional value. The BI values of groundnut paste samples from the various markets are Kotokuraba (126.47 ± 4.16), Mankessim (108.83 ± 12.48), Twifo Praso (97.06 ± 4.16), Swedru (135.3 ± 0.0), and Kasoa (91.18 ± 4.16), with a range of 88.23 to 135.29. High BI values, like those of Swedru and Kotokuraba, indicate significant browning due to intense roasting, enhancing flavour and colour but potentially forming harmful compounds such as acrylamide, posing food safety concerns (Friedman, 2015). Moderate BI values, as seen in Mankessim, suggest

balanced browning, desirable for flavour without excessive risk(Shapla et al., 2018). Twifo Praso's lower BI indicates milder roasting, leading to a lighter colour and milder flavour, appealing to some consumers but possibly lacking depth (Adrian, 2019). Kasoa's low BI suggests minimal browning, enhancing safety but potentially reducing flavour intensity. These variations highlight the importance of controlling BI to balance flavour, appearance, and safety, ensuring high-quality groundnut paste that meets consumer preferences (Blutinger, 2022).

Based on the Browning Index (BI) analysis, Mankessim's groundnut paste, with a BI of 108.83 ± 12.48, appears to be the best option. This moderate BI suggests a balanced degree of browning, which is desirable for flavour enhancement without excessive risk of forming harmful compounds like acrylamide (Shapla et al., 2018). Mankessim's paste achieves a good balance between intense flavour and appealing colour, while maintaining a lower risk of overprocessing, thus ensuring both quality and safety. This balance is likely to meet consumer preferences effectively, making Mankessim's groundnut paste the recommended choice.

Determination of fungal count on groundnut paste

The samples were inoculated onto potato dextrose agar (PDA) to determine the colony-forming unit of the organisms present in the groundnut paste samples. The mean fungal counts of the samples from the various markets on PDA ranged from 1.60 – 2.48 $\log_{10}$CFU/g (Table 9). The lower fungal count was observed in Samples from the Swedru market while the higher fungal count was seen in samples from the Kasoa market.

Table 8: Fungal count on commercial groundnut pastes on PDA.

Samples	Market values (log_{10} CFU/g)
Kotokuraba	2.08 ± 1.45
Mankessim	2.00 ± 0.00
Twifo Praso	2.38 ± 1.75
Swedru	1.60 ± 0.00
Kasoa	2.48 ± 1.85
GS 955:2019	**10**

Groundnut pastes are prone to mycotoxin contamination and fungal infection just like any other crop. Diao et al., (2017), defined mycotoxins as a toxic chemical agent formed as a secondary metabolite by filamentous fungi. According to the Ghana Standard Authority, a groundnut paste is considered safe for consumption when the fungal count falls within the range of 10 to 100. The present study shows the fungal count diversity across the groundnut paste samples. The Colony Forming Unit (CFU) in this study falls within the range of Ghana Standard Authority regulation. The CFU observed in this study was comparable to that of the International Commission on Microbiological Specification for Food (ICMSF) which proposed 10^4 – 10^5 CFU/g (4.0 – 5.0 log_{10}CFU/g) as tolerable and ≥ 10^6 CFU/g (≥ 6.0 log_{10}CFU/g) as unacceptable for ready-to-eat foods (Roberts et al., 1996). Accordingly, the study's observed degree of contamination is deemed acceptable by the proposed standards. The low fungal count observed in this study could be due to the presence of low moisture content in the groundnut paste which has created an unsuitable condition for microbial growth (Table 9). However, studies have also demonstrated that the climate in subtropical

areas which includes high temperature, rainfall and humidity contributes massively to fungal growth and mycotoxin contamination in peanuts as reported (Payne, 2016).

From the study, it can be concluded that samples from Kotokuraba, Mankessim, Twifo Praso, Swedru and Kasoa markets respectively fall within the safety range of peanut products as recommended by Ghana Standard Authority (GSA) and the International Commission of Microbiological Specification for Foods (ICMFS). Nevertheless, these results could be explained by good conditions under which peanut paste is made including seed sorting, roasting, milling, packaging and transportation of groundnut paste under recommended conditions. According to (Fandohan et al., 2008), practices such as sorting help reduce fungal contamination of products. In addition, Mutegi et al. (2009) reported that poor transportation conditions and marketing of peanut products can contribute to microbial growth.

Spectral Examination of groundnut paste with cassava flour and groundnut paste with roasted maize flour.

The Partial Least Squares (PLS) model was employed to analyze the spectral data of groundnut paste adulterated with cassava flour and roasted maize flour. The raw preprocessing technique was applied, and the results are summarized in Table 10 and Figures 5 and 6.

For groundnut paste adulterated with cassava flour, the PLS model achieved a coefficient of determination (R^2) of 0.8846 during training, indicating a strong fit between the predicted and actual values. The Standard Error of Calibration (SEC) was 10.4631, and the bias during training was 1.0515, reflecting minor deviations in prediction. When applied to the testing

data, the model maintained a consistent R^2 of 0.884, demonstrating its robustness and generalization capability. However, the Standard Error of Prediction (SEP) was slightly lower at 10.4368, and the bias increased to 1.6104, suggesting a small underestimation during testing. The Residual Predictive Deviation (RPD) value of 2.9713 indicates moderate predictive power, and the Range Error Ratio (RER) of 9.5815 suggests that the model is reasonably effective in capturing the variance in the data.

Nevertheless, with groundnut paste adulterated with roasted maize flour, the PLS model demonstrated better performance. The R^2 during training was higher at 0.9405, indicating a more accurate fit between the predicted and actual values. The SEC was lower at 7.5152, and the training bias was reduced to 0.7553, reflecting improved calibration. During testing, the model achieved an R^2 of 0.8984, slightly lower than the training R^2 but still indicating strong predictive power. The SEP increased to 9.7645, and the testing bias was 1.5067, slightly better than the cassava flour model. The RPD of 3.1759 and RER of 10.2411 further suggest that the model has good predictive accuracy and is effective at capturing the variance in the data.

Overall, the PLS model demonstrated strong performance in detecting adulteration in groundnut paste when raw preprocessing was applied, with better results observed for roasted maize flour compared to cassava flour. The differences in R^2, SEC, SEP, bias, RPD, and RER values between the two adulterants indicate that the model's effectiveness varies depending on the type of adulteration, with roasted maize flour being more accurately predicted.

Table 9: Raw preprocessing technique of groundnut paste adulterated with cassava flour and roasted maize flour using the PLS model.

Preprocessing	R^2 (Training)	SEC	Bias (Training)	R^2 (Testing)	SEP	Bias (Testing)	RPD	RER
Raw (Cassava flour)	0.8846	10.4631	1.0515	0.884	10.4368	1.6104	2.9713	9.5815
Raw (Roasted Maize flour)	0.9405	7.5152	0.7553	0.8984	9.7645	1.5067	3.1759	10.2411

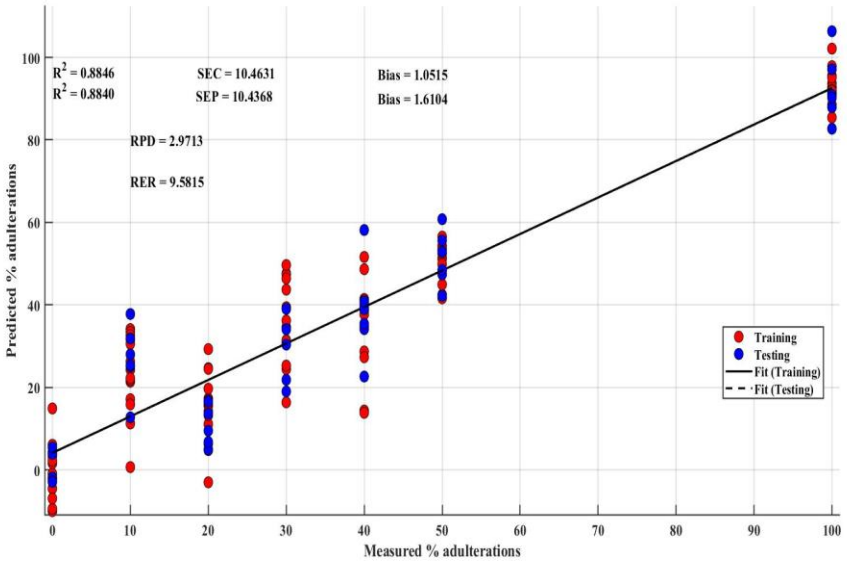

Figure 6: Raw preprocessing technique of groundnut paste adulterated with cassava flour.

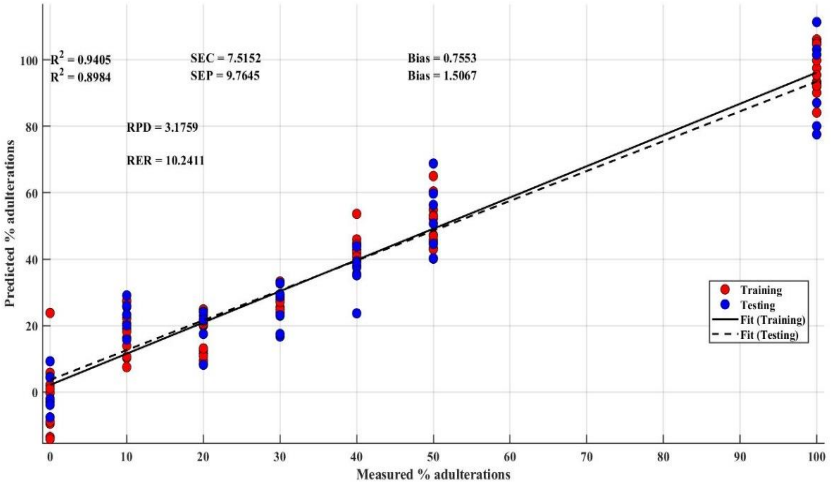

Figure 7: Raw preprocessing technique of groundnut paste adulterated with roasted maize flour.

Performance Comparison of PLS and SVMR Models on Mean-Centered Spectral Data of Adulterated Groundnut Paste.

The study utilized Partial Least Squares (PLS) and Support Vector Machine Regression (SVMR) models to analyze the spectral data of groundnut

paste adulterated with cassava flour and roasted maize flour, following mean centring (MC) preprocessing. The results are presented in Table 10.

For groundnut paste adulterated with cassava flour, the PLS model achieved a training R^2 of 0.8578, suggesting a good fit between the predicted and actual values during the training phase. The Standard Error of Calibration (SEC) was 11.6138, and the bias during training was 1.1672, indicating some degree of prediction error. When applied to the test data, the model's R^2 dropped to 0.8239, demonstrating a slight decline in predictive power. The Standard Error of Prediction (SEP) increased to 12.8566, reflecting a higher error rate in the test set. The bias remained constant at 12.8566, and the Residual Predictive Deviation (RPD) of 2.4121 suggests moderate predictive capability. The Range Error Ratio (RER) of 7.7781 indicates that the model's accuracy is adequate but not highly reliable.

Groundnut paste adulterated with roasted maize flour, the PLS model showed stronger performance. The training R^2 was higher at 0.9300, indicating a better fit. The SEC was lower at 8.1507, and the training bias was 0.8191, reflecting improved calibration accuracy. On the test data, the model maintained a high R^2 of 0.9149, showing strong generalization to unseen data. The SEP was 8.9382, and the test bias was slightly higher at 1.3792, indicating that the model slightly underestimates the predictions. The RPD value of 3.4695 indicates good predictive power, and the RER of 11.1879 suggests that the model is effective at capturing the variance in the data.

Groundnut paste adulterated with cassava flour, the SVMR model outperformed the PLS model significantly. The training R^2 was 0.9751, reflecting an excellent fit between the predicted and actual values. The SEC

was significantly lower at 6.0924, indicating better calibration accuracy. The training bias was minimal at 0.6123. On the test data, the SVMR model did not provide an R^2 value; however, the SEP was much lower at 5.6338, suggesting superior predictive accuracy compared to the PLS model. The bias remained at 5.6338. The RPD of 5.5044 and the RER of 17.7500 demonstrate the model's strong predictive power and reliability in detecting cassava flour adulteration.

Similarly, the SVMR model for groundnut paste adulterated with roasted maize flour also showed exceptional performance. The training R^2 was 0.9753, indicating a very strong fit. The SEC was low at 6.1211, and the training bias was minimal at 0.6152. The test R^2 was 0.9798, showing excellent generalization capability. The SEP was 5.6846, and the test bias was 0.8772, indicating minimal error. The RPD of 5.4552 and the RER of 17.5913 highlight the model's robust performance and high reliability in detecting roasted maize flour adulteration.

The results indicate that the SVMR model, particularly with mean centring preprocessing, outperforms the PLS model in detecting both cassava flour and roasted maize flour adulteration in groundnut paste. The SVMR model's higher R^2 values, lower SEC and SEP, and higher RPD and RER values demonstrate its superior predictive accuracy and reliability compared to the PLS model. This suggests that SVMR is a more effective machine-learning technique for this specific application, especially when dealing with the complexity and variability in the spectral data of adulterated groundnut paste.

Table 10: Mean Centering preprocessing technique of groundnut paste adulterated with cassava flour and roasted maize flour using PLS and SVMR model.

Preprocessing	R^2 (Train)	SEC	Bias (Train)	R^2 (Test)	SEP	Bias (Test)	RPD	RER
MC (Cassava flour) PLS	0.8578	11.6138	1.1672	0.8239	12.8566	12.8566	2.4121	7.7781
MC (Roasted Maize flour) PLS	0.9300	8.1507	0.8191	0.9149	8.9382	1.3792	3.4695	11.1879
MC (Cassava flour) SVMR	0.9751	6.0924	0.6123	0.9796	5.6338	0.8693	5.5044	17.7500
MC (Roasted Maize flour) SVMR	0.9753	6.1211	0.6152	0.9798	5.6846	0.8772	5.4552	17.5913

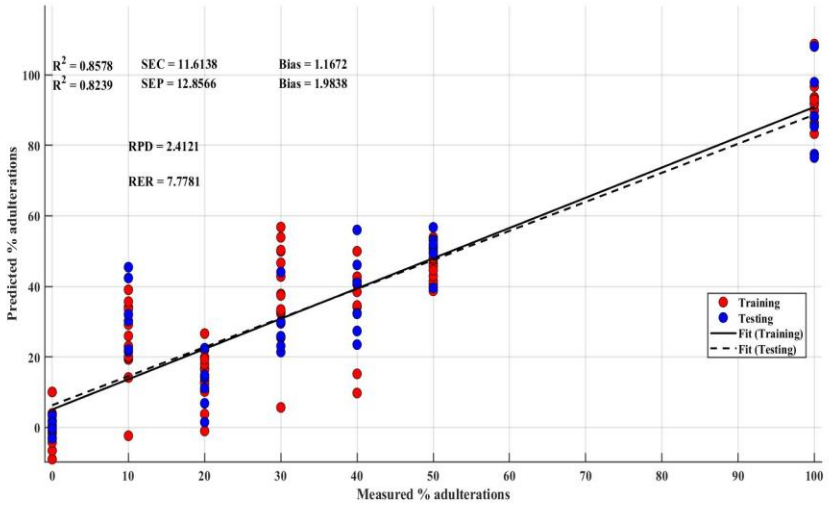

Figure 8: Mean Centering preprocessing technique of groundnut paste adulterated with cassava flour.

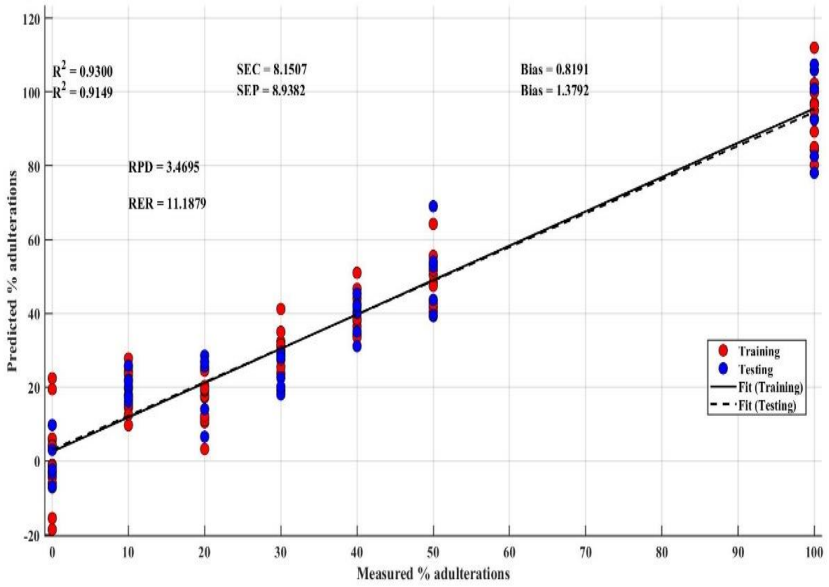

Figure 9: Mean Centering preprocessing technique of groundnut paste adulterated with Roasted Maize flour.

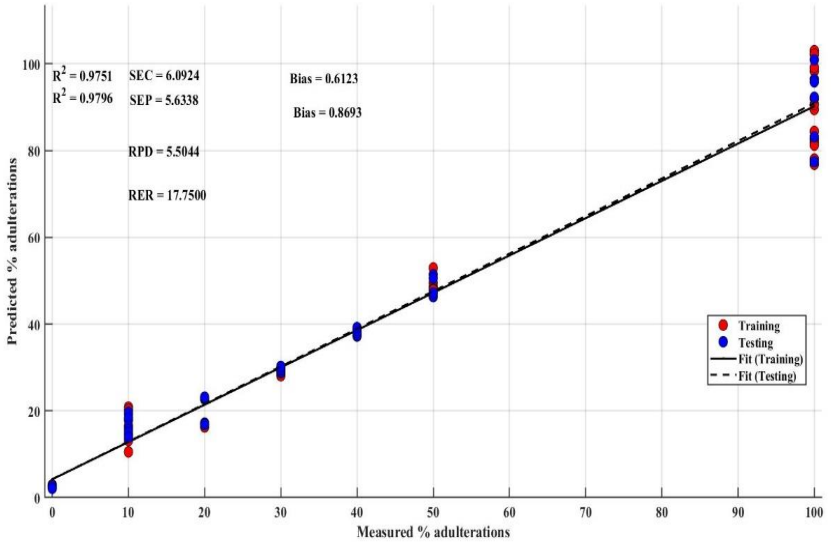

Figure 10: Mean Centering preprocessing technique and Support vector machine regression model of groundnut paste adulterated with cassava flour.

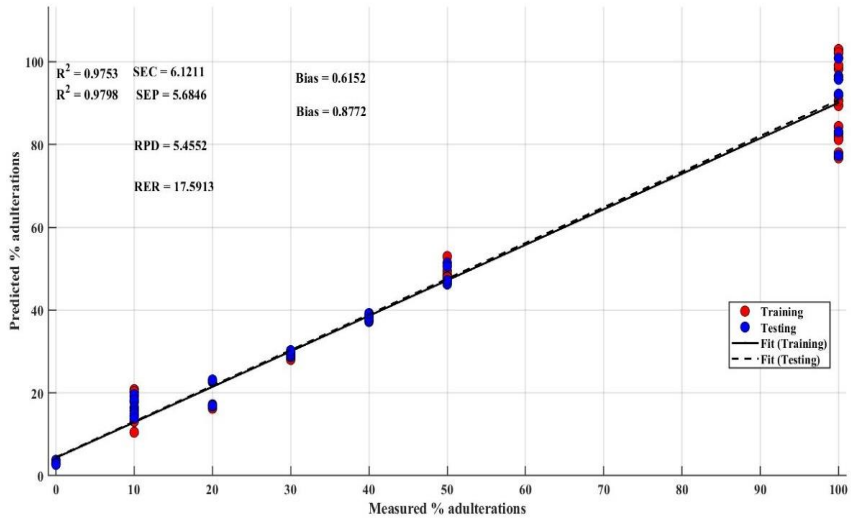

Figure 11: Mean Centering preprocessing technique and Support vector machine regression model of groundnut paste adulterated with roasted maize flour.

Comparative Analysis of PLS and SPA-PLS Models on MSC Preprocessed Spectral Data of Adulterated Groundnut Paste.

This study employed Partial Least Squares (PLS) and Successive Projections Algorithm Partial Least Squares (SPA-PLS) models to analyze the spectral data of groundnut paste adulterated with cassava flour and roasted

maize flour, using Multiplicative Scatter Correction (MSC) preprocessing. For the groundnut paste adulterated with cassava flour, the PLS model showed a training R^2 of 0.8623, indicating a good fit during the training phase. The Standard Error of Calibration (SEC) was 11.4296, and the training bias was 1.1487, suggesting some prediction error. On the test data, the model's R^2 slightly decreased to 0.8578, indicating a consistent performance with the training data. The Standard Error of Prediction (SEP) was 11.5540, and the bias during testing was higher at 1.7828, reflecting an increase in prediction error on unseen data. The Residual Predictive Deviation (RPD) of 2.6840 implies moderate predictive ability, while the Range Error Ratio (RER) of 8.6550 indicates that the model has an acceptable level of accuracy, though there is room for improvement.

In the case of groundnut paste adulterated with roasted maize flour, the PLS model showed a better performance than with cassava flour. The training R^2 was 0.8983, indicating a stronger correlation between the predicted and actual values. The SEC was lower at 9.8209, and the training bias was 0.9870, reflecting better calibration accuracy. For the test data, the R^2 improved to 0.9310, showing strong generalization capability. The SEP was 8.0510, and the bias during testing was 1.2423, indicating a relatively low error. The RPD of 3.8518 and the RER of 12.4208 suggest that the model is effective at capturing the variance in the data, making it reliable for detecting roasted maize flour adulteration.

The SPA-PLS model, when applied to groundnut paste adulterated with cassava flour, performed less effectively compared to the PLS model. The training R^2 was 0.7877, indicating a weaker fit. The SEC was higher at

14.1907, and the training bias increased to 1.4261, signifying greater prediction error. On the test data, the R^2 dropped to 0.7384, showing a notable decline in predictive power. The SEP rose significantly to 15.6706, and the testing bias increased to 2.4180, indicating considerable error in the predictions. The RPD of 1.9789 suggests low predictive capability, while the RER of 6.3814 indicates that the model's accuracy is insufficient for reliable detection of cassava flour adulteration.

However, with groundnut paste with roasted maize flour adulteration, the SPA-PLS model also demonstrated lower performance. The training R^2 was 0.7733, showing a weaker fit compared to the PLS model. The SEC was 14.6636, and the training bias was 1.4737, indicating significant prediction error. On the test data, the R^2 further declined to 0.7175, suggesting poor generalization ability. The SEP increased to 16.2849, and the testing bias rose to 2.5128, reflecting substantial error in predictions. The RPD of 1.9043 and the RER of 6.1406 confirm that the model has low predictive power and reliability for detecting roasted maize flour adulteration.

The results demonstrate that the PLS model with MSC preprocessing outperformed the SPA-PLS model in detecting both cassava flour and roasted maize flour adulteration in groundnut paste. The PLS model exhibited higher R^2 values, lower SEC and SEP, and better RPD and RER values compared to the SPA-PLS model. This suggests that the PLS model is more effective and reliable for this specific application, especially when MSC preprocessing is applied. The SPA-PLS model, while useful, did not achieve the same level of accuracy and predictive power, particularly in the presence of noise and

variability in the spectral data. Therefore, the PLS model is recommended for future studies involving the detection of food adulteration using spectral data.

Table 11: Multiplicative Scattering Correction preprocessing technique of groundnut paste adulterated with cassava flour and groundnut paste adulterated with roasted maize flour using PLS and SPA- PLS model.

Preprocessing	R^2 (Train)	SEC	Bias (Train)	R^2 (Test)	SEP	Bias (Test)	RPD	RER
MSC (Cassava flour) -PLS	0.8623	11.4296	1.1487	0.8578	11.5540	1.7828	2.6840	8.6550
MSC (Roasted Maize flour)-PLS	0.8983	9.8209	0.9870	0.9310	8.0510	1.2423	3.8518	12.4208
MSC (Cassava flour) SPA-PLS	0.7877	14.1907	1.4261	0.7384	15.6706	2.4180	1.9789	6.3814
MSC (Roasted Maize flour) SPA-PLS	0.7733	14.6636	1.4737	0.7175	16.2849	2.5128	1.9043	6.1406

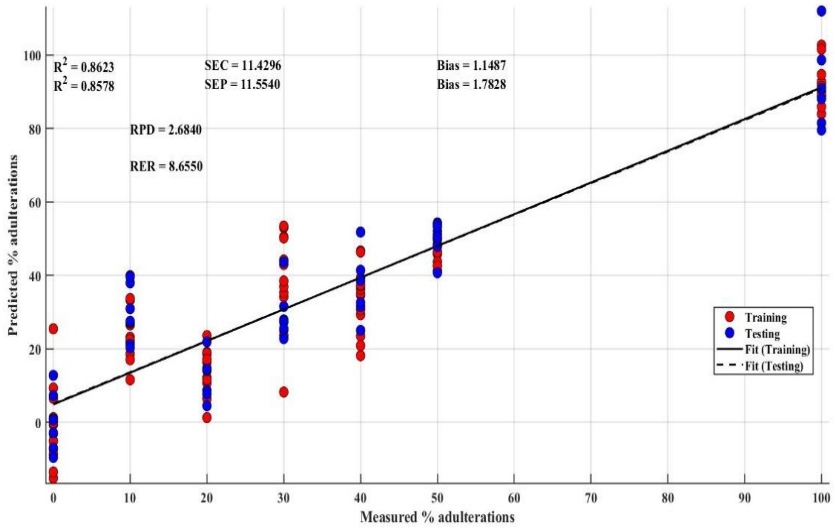

Figure 12: Multiplicative Scattering Correction preprocessing technique and PS model of groundnut paste adulterated with cassava flour.

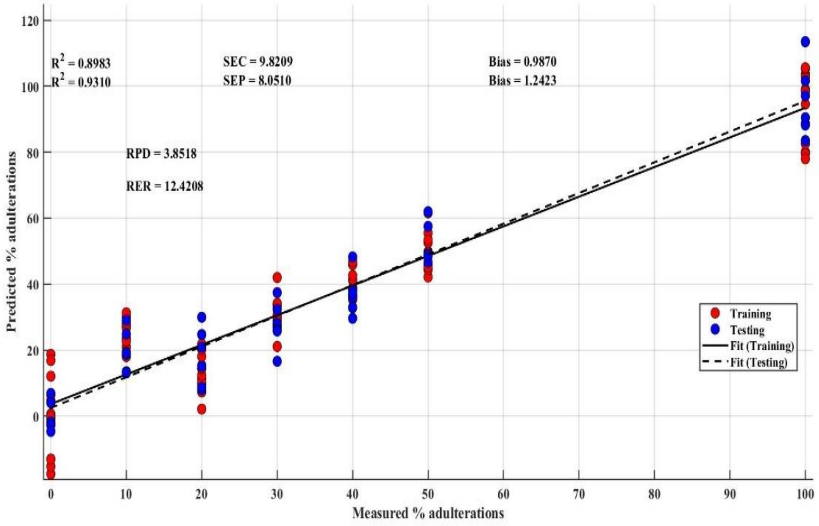

Figure 13: Multiplicative Scattering Correction preprocessing technique and PLS model of groundnut paste adulterated with roasted maize flour.

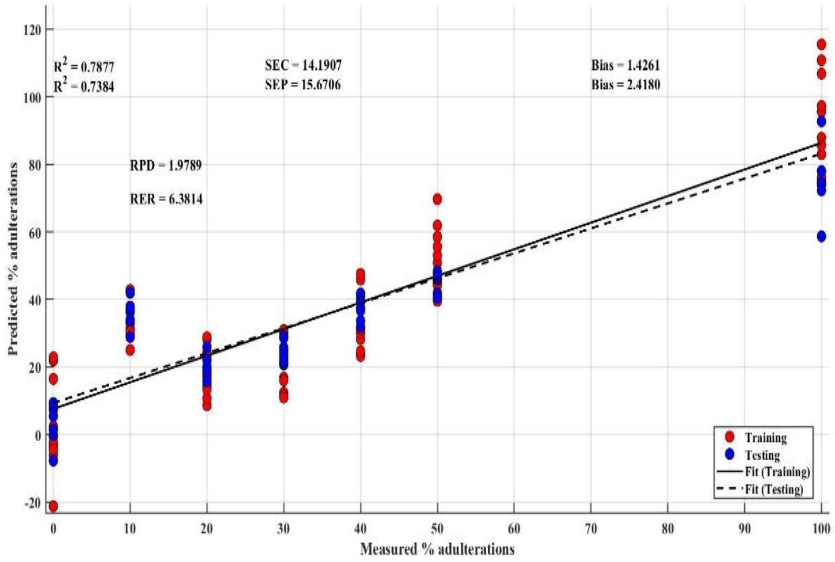

Figure 14: Multiplicative Scattering Correction preprocessing technique and SPA-PLS model of groundnut paste adulterated with cassava flour.

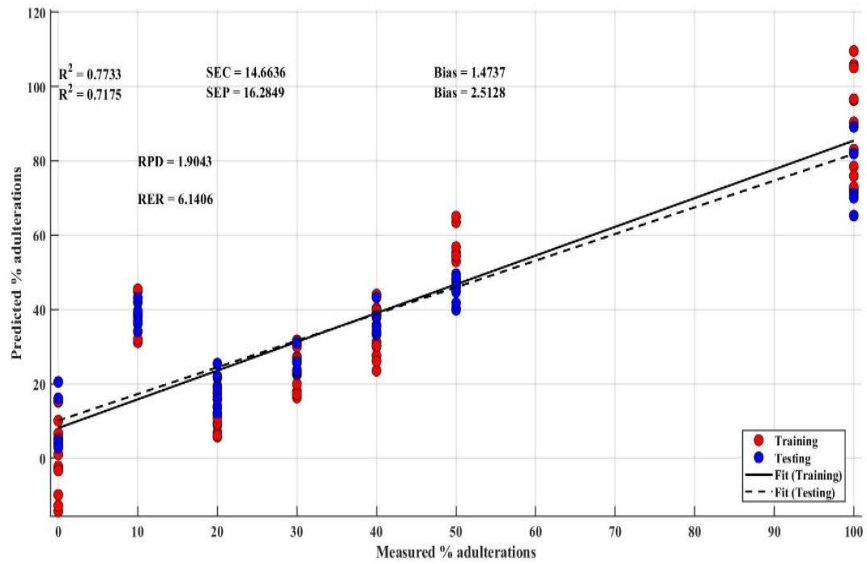

Figure 15: Multiplicative Scattering Correction preprocessing technique and SPA-PLS model of groundnut paste adulterated with roasted maize flour.

Evaluation of PLS and SPA-PLS Models with SNV Preprocessing for Adulteration Detection in Groundnut Paste.

This study utilized Partial Least Squares (PLS) and Successive Projections Algorithm Partial Least Squares (SPA-PLS) models to analyze

spectral data from groundnut paste adulterated with cassava flour and roasted maize flour, using Standard Normal Variate (SNV) preprocessing. For groundnut paste adulterated with cassava flour, the PLS model showed strong performance with a training R^2 of 0.8852, indicating a good fit during the training phase. The Standard Error of Calibration (SEC) was 10.4345, and the bias during training was 1.0487, suggesting a reasonable degree of prediction accuracy. On the test data, the model maintained a high R^2 of 0.8894, demonstrating consistent predictive power. The Standard Error of Prediction (SEP) was 10.1893, slightly lower than the SEC, and the testing bias was 1.5722, indicating some error in predictions. The Residual Predictive Deviation (RPD) of 3.0435 suggests moderate to good predictive capability, and the Range Error Ratio (RER) of 9.8142 indicates that the model has a reliable level of accuracy for detecting cassava flour adulteration.

For groundnut paste adulterated with roasted maize flour, the PLS model exhibited superior performance. The training R^2 was 0.9278, indicating a strong fit between the predicted and actual values. The SEC was lower at 8.2770, and the training bias was minimal at 0.8318, reflecting high calibration accuracy. The model's R^2 on the test data further improved to 0.9565, demonstrating excellent generalization capability. The SEP was 6.3882, indicating a lower prediction error, and the test bias was slightly higher at 0.9857. The RPD value of 4.8544 suggests strong predictive power, and the RER of 15.6540 indicates high reliability in detecting roasted maize flour adulteration.

The SPA-PLS model showed a slightly lower performance compared to the PLS model when applied to cassava flour adulteration. The training R^2

was 0.8492, indicating a good fit, though slightly weaker than the PLS model. The SEC was 11.9611, higher than that of the PLS model, suggesting lower calibration accuracy. The bias during training was 1.2021. The model achieved the same R^2 of 0.8894 on the test data as the PLS model, indicating that it generalized equally well. The SEP was 10.1893, identical to the PLS model, with a testing bias of 1.5722. The RPD value of 3.0435 matches the PLS model, indicating similar predictive capability.

The SPA-PLS model for roasted maize flour also showed good performance, though not as strong as the PLS model. The training R^2 was 0.8693, indicating a good but slightly weaker fit. The SEC was 11.1341, higher than in the PLS model, and the training bias was 1.1190, indicating a slightly higher prediction error. The model maintained a high R^2 of 0.9565 on the test data, matching the PLS model's performance. The SEP was 6.3882, identical to the PLS model, and the test bias was 0.9857. The RPD value of 4.8544 suggests strong predictive power, similar to the PLS model.

The analysis indicates that the PLS model generally outperforms the SPA-PLS model when using SNV preprocessing, particularly for detecting roasted maize flour adulteration. The higher R^2 values, lower SEC and SEP, and higher RPD and RER values in the PLS model for roasted maize flour suggest it is more reliable and accurate than the SPA-PLS model. However, both models show moderate performance for cassava flour adulteration, with neither model demonstrating a clear advantage. Overall, the PLS model with SNV preprocessing is recommended for detecting adulteration in groundnut paste, especially for roasted maize flour.

Table 12: Standard Normal Variant preprocessing technique of groundnut paste adulterated with cassava flour and groundnut paste adulterated with roasted maize flour using the PLS model.

Preprocessing	R^2 (Train)	SEC	Bias (Train)	R^2 (Test)	SEP	Bias (Test)	RPD	RER
SNV (Cassava flour) PLS	0.8852	10.4345	1.0487	0.8894	10.1893	1.5722	3.0435	9.8142
SNV (Roasted Maize flour) PLS	0.9278	8.2770	0.8318	0.9565	6.3882	0.9857	4.8544	15.6540
SNV (Cassava flour) SPA-PLS	0.8492	11.9611	1.2021	0.8894	10.1893	1.5722	3.0435	
SNV (Roasted Maize flour) SPA-PLS	0.8693	11.1341	1.1190	0.9565	6.3882	0.9857	4.8544	

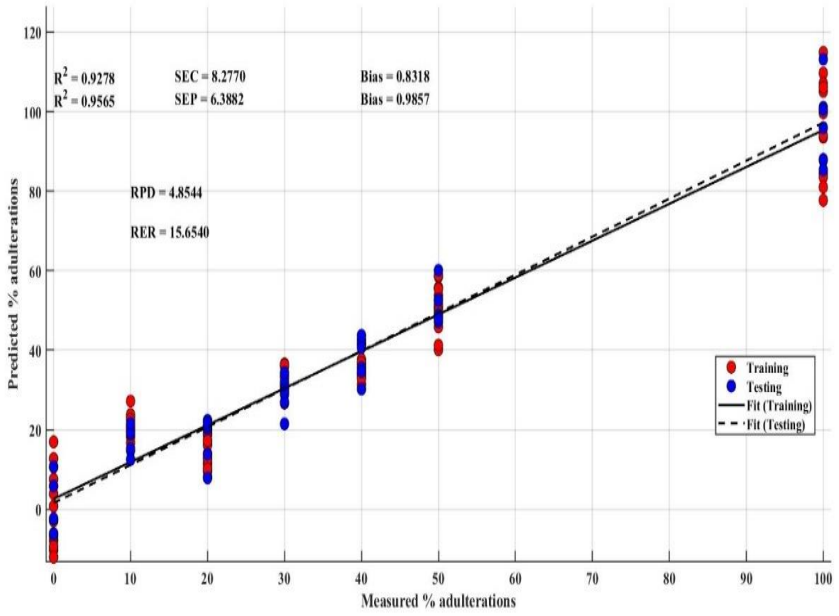

Figure 16: Standard Normal Variant preprocessing technique and PLS model of groundnut paste adulterated with cassava flour.

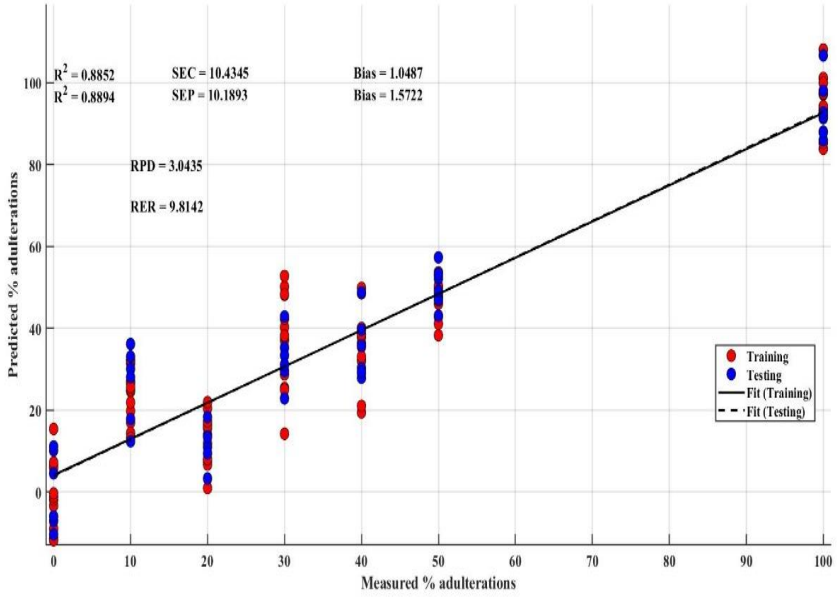

Figure 17: Standard Normal Variant preprocessing technique and PLS model of groundnut paste adulterated with roasted maize flour.

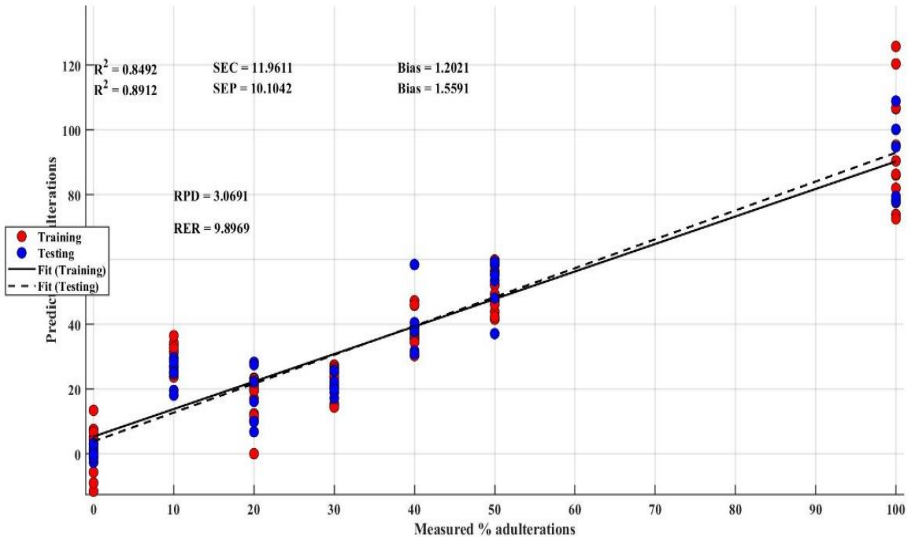

Figure 18: Standard Normal Variant preprocessing technique and PLS model of groundnut paste adulterated with cassava flour.

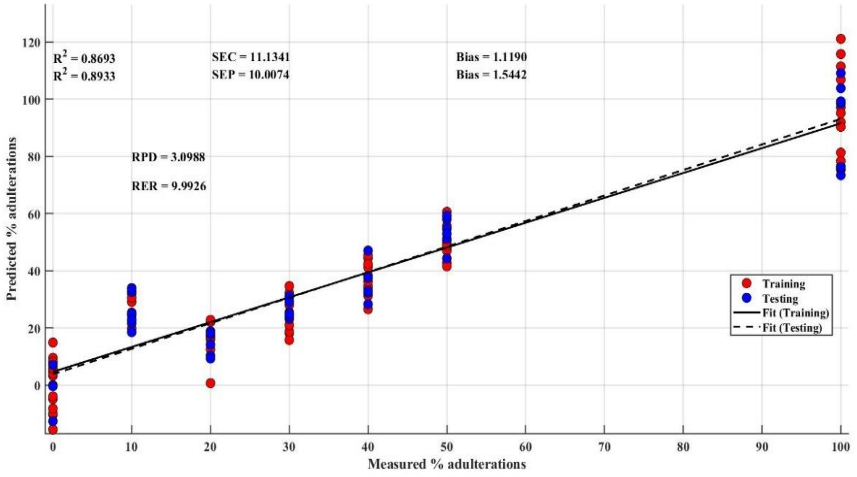

Figure 19: Standard Normal Variant preprocessing technique and PLS model of groundnut paste adulterated with roasted maize flour.

Performance Evaluation of PLS and SPA-PLS Models with First Derivative Preprocessing for Adulteration Detection in Groundnut Paste.

This section discusses the performance of Partial Least Squares (PLS) and Successive Projections Algorithm Partial Least Squares (SPA-PLS) models in detecting adulteration in groundnut paste with cassava flour and roasted maize flour, using First Derivative (FD) preprocessing. The results, as

detailed in the table, demonstrate the effectiveness of these models in this context. For cassava flour adulteration, the PLS model demonstrated a strong predictive ability. The model achieved a high R^2 of 0.9265 during the training phase, indicating a strong correlation between the predicted and actual values. The Standard Error of Calibration (SEC) was 8.3465, and the bias during training was relatively low at 0.8388, suggesting a good fit with minimal error.

However, the model's performance on the test data saw a slight decline, with an R^2 of 0.8638, which still reflects a strong generalization capability. The Standard Error of Prediction (SEP) increased to 11.3057, indicating a higher prediction error on the test data, and the bias during testing was 1.7445, reflecting some underestimation of the predictions. The Residual Predictive Deviation (RPD) of 2.7429 suggests moderate predictive power, while the Range Error Ratio (RER) of 8.8451 indicates reasonable reliability in detecting cassava flour adulteration.

The PLS model performed notably better in detecting roasted maize flour adulteration. The training R^2 was 0.9390, indicating a very strong fit between the predicted and actual values, with a lower SEC of 7.6058 and a minimal bias of 0.7644 during training. The model's performance remained robust on the test data, with an R^2 of 0.9460, showing excellent generalization. The SEP was lower at 7.1183, and the bias during testing was 1.0984, reflecting accurate predictions with minimal error. The RPD value of 4.3565 indicates strong predictive capability and the RER of 14.0483 suggests that the model is highly reliable in detecting roasted maize flour adulteration.

The SPA-PLS model demonstrated superior performance compared to the PLS model for cassava flour adulteration. It achieved a higher training R^2

of 0.9416, indicating an excellent fit between predicted and actual values. The SEC was lower at 7.4443, and the training bias was minimal at 0.7481, suggesting higher calibration accuracy. On the test data, the SPA-PLS model performed exceptionally well, with an R^2 of 0.9601, reflecting strong generalization. The SEP was significantly lower at 6.1209, indicating reduced prediction error, and the testing bias was also low at 0.9445. The RPD value of 5.0663 indicates good predictive power, and the RER of 16.3373 highlights the model's high reliability in detecting cassava flour adulteration.

For roasted maize flour adulteration, the SPA-PLS model also demonstrated excellent performance. The training R^2 was 0.9361, indicating a strong fit, with an SEC of 7.7830 and a training bias of 0.7822. The model's generalization to test data was strong, with an R^2 of 0.9603. The SEP was low at 6.1043, and the testing bias was minimal at 0.9419, reflecting accurate predictions. The RPD value of 5.0802 and the RER of 16.3819 further confirm the model's robustness and reliability in detecting roasted maize flour adulteration.

The results indicate that both the PLS and SPA-PLS models perform well in detecting cassava flour and roasted maize flour adulteration in groundnut paste when the first derivative preprocessing is applied. However, the SPA-PLS model consistently outperforms the PLS model in terms of predictive accuracy, as evidenced by higher R^2 values, lower SEP, and higher RPD and RER values. This suggests that the SPA-PLS model, particularly with first derivative preprocessing, is more effective and reliable for this specific application.

Table 13: First Derivative preprocessing technique of groundnut paste adulterated with cassava flour and also groundnut paste adulterated with roasted maize flour using PLS and SPA -PLS model.

Preprocessing	R^2 (Train)	SEC	Bias (Train)	R^2 (Test)	SEP	Bias (Test)	RPD	RER
FD (Cassava flour) -PLS	0.9265	8.3465	0.8388	0.8638	11.3057	1.7445	2.7429	8.8451
FD (Roasted Maize flour) -PLS	0.9390	7.6058	0.7644	0.9460	7.1183	1.0984	4.3565	14.0483
FD (Cassava flour) SPA-PLS	0.9416	7.4443	0.7481	0.9601	6.1209	0.9445	5.0663	16.3373
FD (Roasted Maize flour) SPA-PLS	0.9361	7.7830	0.7822	0.9603	6.1043	0.9419	5.0802	16.3819

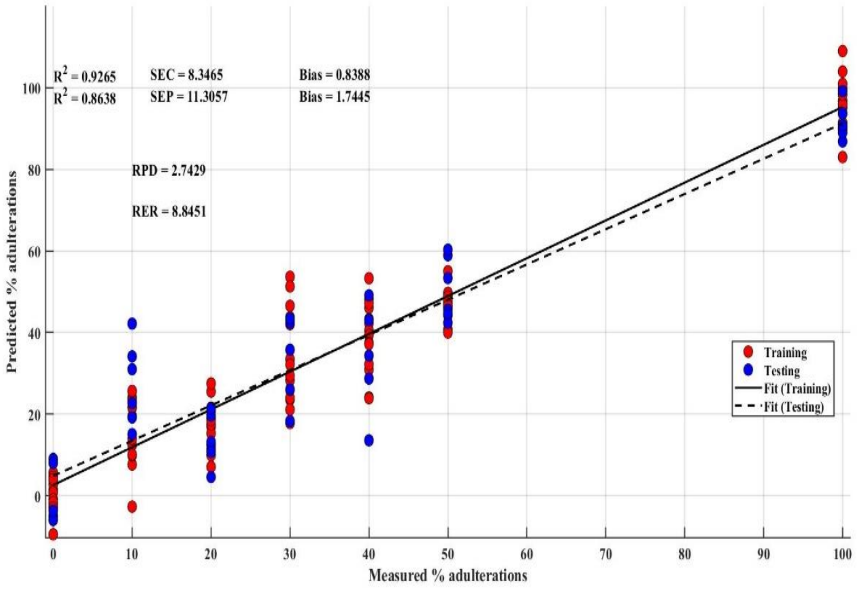

Figure 20: First Derivative preprocessing technique and PLS model of groundnut paste adulterated with cassava flour.

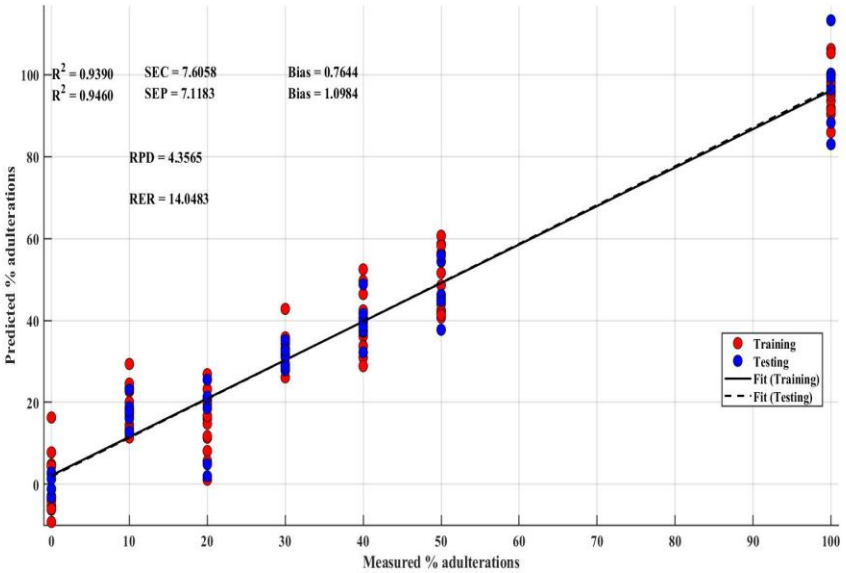

Figure 21: First Derivative preprocessing technique and PLS model of groundnut paste adulterated with roasted maize flour.

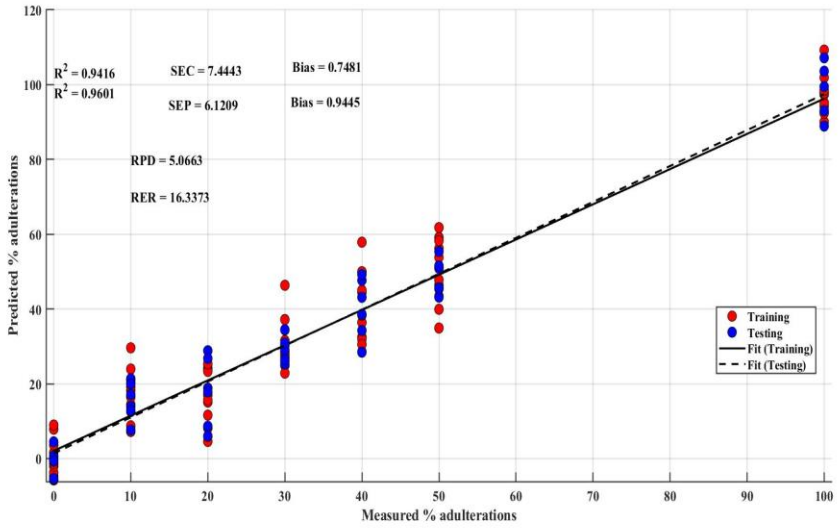

Figure 22: First Derivative preprocessing technique and SPA-PLS model of groundnut paste adulterated with cassava flour.

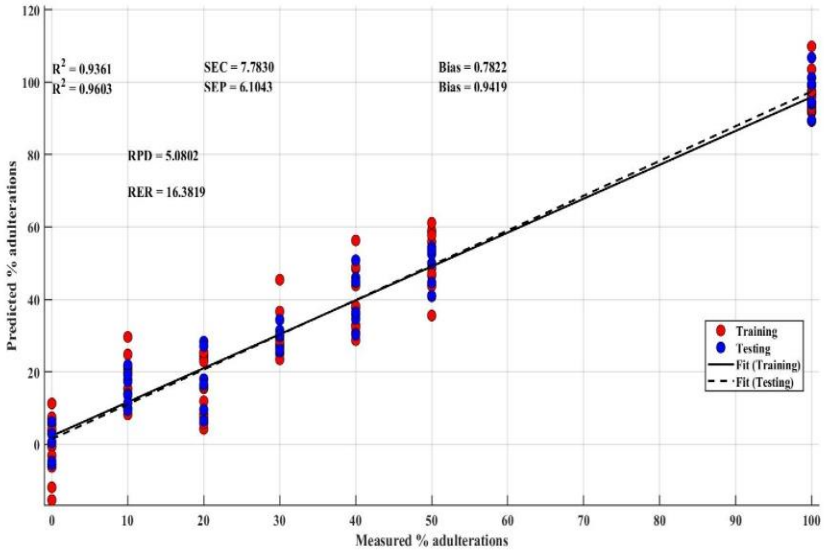

Figure 23: First Derivative preprocessing technique and SPA- PLS model of groundnut paste adulterated with roasted maize flour.

Evaluation of PLS and SPA-PLS Models with Second Derivative (SD) Preprocessing for Adulteration Detection in Groundnut Paste.

This section presents the performance analysis of Partial Least Squares (PLS) and Successive Projections Algorithm Partial Least Squares (SPA-PLS) models in detecting cassava flour and roasted maize flour adulteration in groundnut paste, using Second Derivative (SD) preprocessing. The results

from the table illustrate how these models perform under different conditions. The PLS model performed well in detecting cassava flour adulteration. During the training phase, the model achieved a high R^2 of 0.9302, indicating a strong correlation between the predicted and actual values. The Standard Error of Calibration (SEC) was 8.1373, and the training bias was relatively low at 0.8178, showing that the model was well-calibrated with minimal error. When applied to the test data, the model's R^2 was 0.9193, reflecting strong predictive power and good generalization capability. The Standard Error of Prediction (SEP) was 8.7055, with a test bias of 1.3433, suggesting a slight underestimation in predictions. The Residual Predictive Deviation (RPD) of 3.5622 indicates good predictive capability, while the Range Error Ratio (RER) of 11.4869 suggests reliable performance in detecting cassava flour adulteration.

The PLS model performed even better when detecting roasted maize flour adulteration. It achieved a very high R^2 of 0.9570 during training, indicating an excellent fit between the predicted and actual values. The SEC was low at 6.3830, and the training bias was minimal at 0.6415, indicating high accuracy. On the test data, the model's R^2 increased to 0.9780, showcasing its strong generalization capability. The SEP was significantly lower at 4.5455, with a minimal test bias of 0.7014, demonstrating highly accurate predictions. The RPD value of 6.8223 indicates strong predictive power, and the RER of 21.9996 highlights the model's exceptional reliability in detecting roasted maize flour adulteration.

The SPA-PLS model also showed good performance for cassava flour adulteration, though slightly less effective than the PLS model. The training R^2

was 0.8913, indicating a strong fit, with an SEC of 10.1558 and a training bias of 1.0206. On the test data, the model's R^2 was slightly higher at 0.9307, reflecting robust predictive capability. The SEP was lower at 8.0642, and the test bias was minimal at 1.2443, suggesting accurate predictions. The RPD value of 3.8455 suggests good predictive capability, and the RER of 12.4004 indicates that the model is reliable in detecting cassava flour adulteration.

For roasted maize flour adulteration, the SPA-PLS model showed slightly lower performance compared to the PLS model. The training R^2 was 0.8760, indicating a good fit, with an SEC of 10.8467 and a training bias of 1.0901. On the test data, the model's R^2 was 0.9160, showing good generalization capability. The SEP was higher at 8.8780, with a test bias of 1.3699, suggesting a slight underestimation in predictions. The RPD value of 3.4930 and the RER of 11.2638 indicate that the model is effective but less robust than the PLS model in detecting roasted maize flour adulteration.

The analysis indicates that the PLS model consistently outperforms the SPA-PLS model when using SD preprocessing, particularly for detecting roasted maize flour adulteration. The higher R^2 values, lower SEC and SEP, and higher RPD and RER values in the PLS model suggest it is more accurate and reliable than the SPA-PLS model. Both models show strong performance for cassava flour adulteration, with the SPA-PLS model demonstrating slightly better predictive accuracy in some aspects. Overall, the PLS model with SD preprocessing is recommended for detecting adulteration in groundnut paste, especially for roasted maize flour.

Table 14: Second Derivative preprocessing technique of groundnut paste adulterated with cassava flour and also groundnut paste adulterated with roasted maize flour using PLS and SPA-PLS model.

Preprocessing	R^2 (Train)	SEC	Bias (Train)	R^2 (Test)	SEP	Bias (Test)	RPD	RER
SD (Cassava flour) PLS	0.9302	8.1373	0.8178	0.9193	8.7055	1.3433	3.5622	11.4869
SD (Roasted Maize flour) PLS	0.9570	6.3830	0.6415	0.9780	4.5455	0.7014	6.8223	21.9996
SD (Cassava flour) SPA-PLS	0.8913	10.1558	1.0206	0.9307	8.0642	1.2443	3.8455	12.4004
SD (Roasted Maize flour) SPA-PLS	0.8760	10.8467	1.0901	0.9160	8.8780	1.3699	3.4930	11.2638

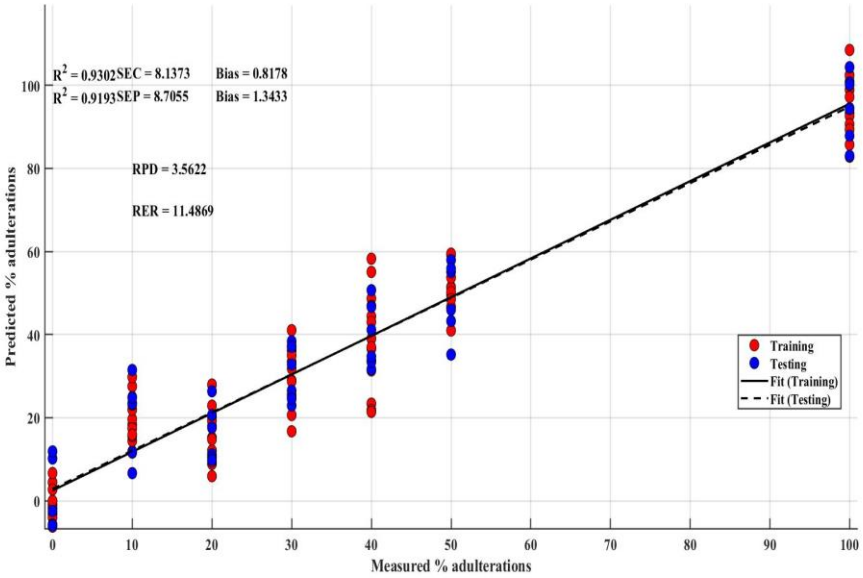

Figure 24: Second Derivative preprocessing technique and PLS model of groundnut paste adulterated with cassava flour.

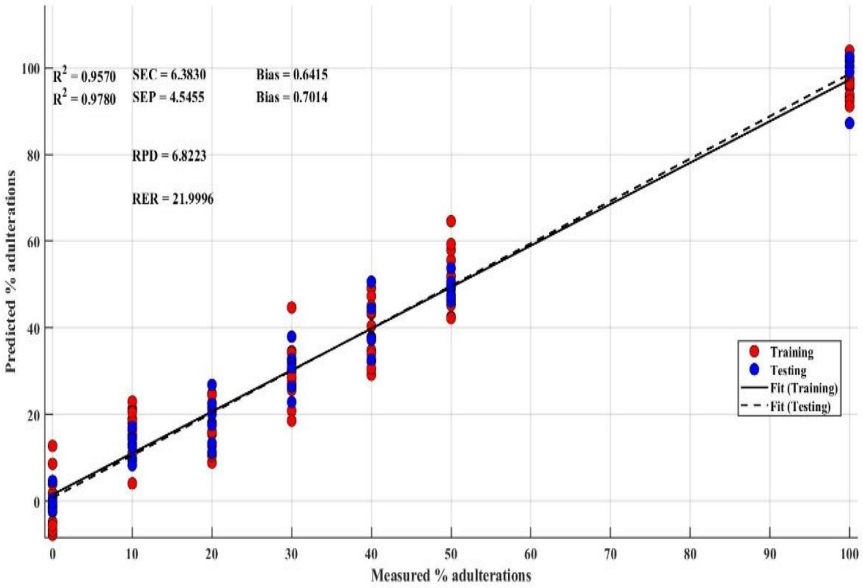

Figure 25: Second Derivative preprocessing technique and PLS model of groundnut paste adulterated with roasted maize flour.

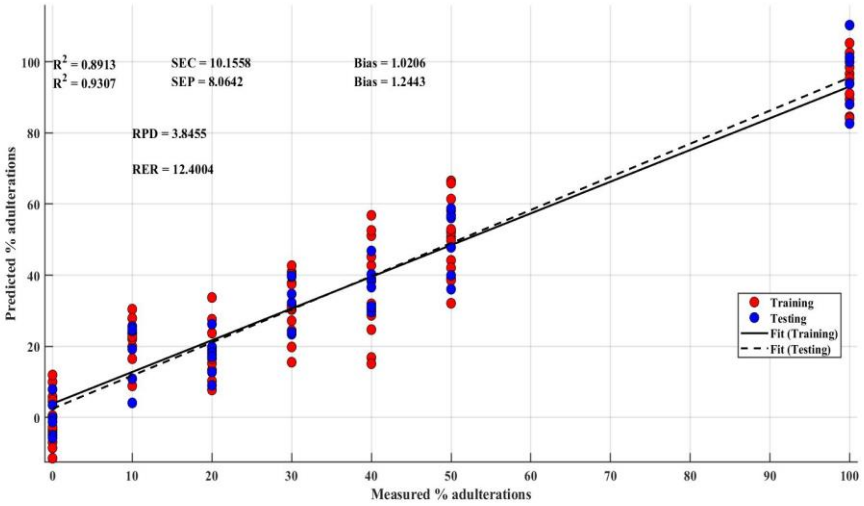

Figure 26: Second Derivative preprocessing technique and SPA- PLS model of groundnut paste adulterated with cassava flour.

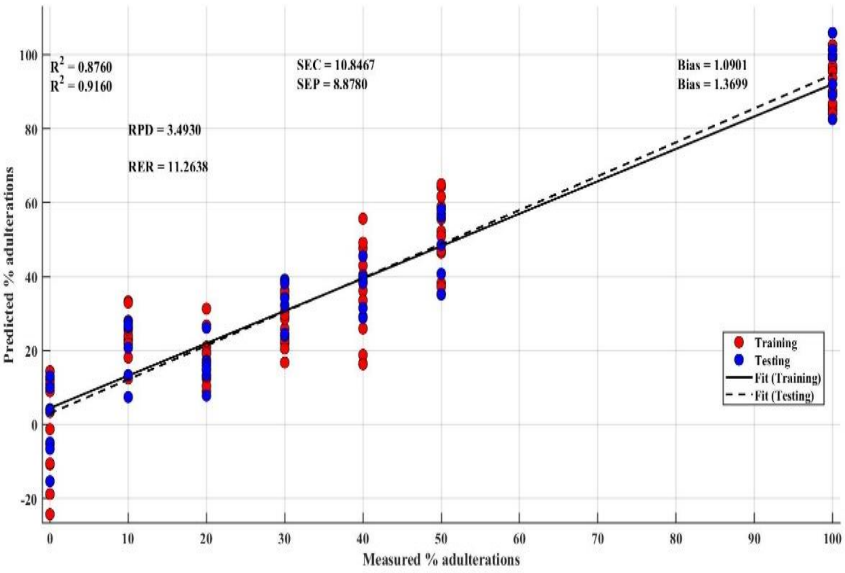

Figure 27: Second Derivative preprocessing technique and SPA- PLS model of groundnut paste adulterated with roasted maize flour.

Principal component analysis (PCA) of adulterated groundnut paste samples

Principal Component Analysis (PCA) was employed to visualize the differentiation between authentic groundnut paste and adulterated groundnut paste with cassava flour and roasted maize flour. The analysis involved

plotting the scores on the first two principal components (PC1 and PC2) to observe the clustering of samples based on their compositional differences.

In the PCA one plot, which compares authentic groundnut paste with samples adulterated with cassava flour, the results show a clear separation between the two groups. Authentic groundnut paste samples, represented by blue dots, cluster on the left side of the plot, while the adulterated samples, represented by red dots, are grouped on the right. This separation is particularly evident along the PC1 axis, which accounts for 99.04% of the total variance. The distinct clustering suggests that the addition of cassava flour significantly alters the spectral properties of groundnut paste, and these changes are effectively captured by the PCA model. The PCA two plot focuses on the comparison between pure groundnut paste and samples adulterated with roasted maize flour. Similar to the first plot, there is a pronounced separation between the pure and adulterated samples along the PC1 axis, which again explains 99.04% of the variance. Pure samples are clustered on the left, while adulterated samples are on the right, indicating that the spectral differences caused by the addition of roasted maize flour are also significant and detectable by the PCA model. The PCA analysis demonstrates its effectiveness in distinguishing between pure groundnut paste and samples adulterated with either cassava flour or roasted maize flour. The clear separation of sample clusters along the first principal component highlights the ability of PCA to detect adulteration in groundnut paste. This capability is essential for ensuring groundnut paste quality and consumer safety, underscoring PCA's value as a tool in groundnut paste adulteration detection.

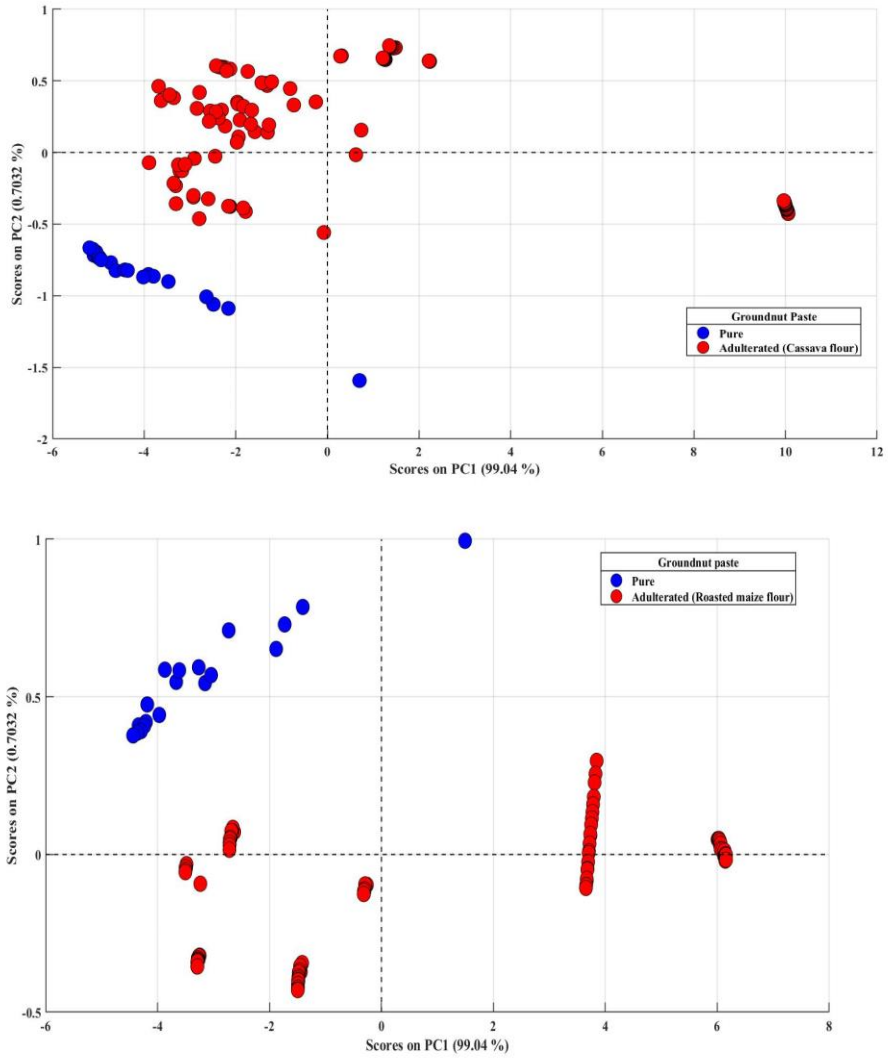

Figure 28: Principal Component Analysis of groundnut paste adulterated with cassava flour and roasted maize flour.

The results from the Partial Least Squares (PLS) model applied to groundnut paste adulterated with cassava flour and roasted maize flour reveal robust performance consistent with established literature. The high R^2 values (0.8846 and 0.9405 for training) indicate a strong model fit. This supports the findings of Esbensen and Romañach (2021), who highlight PLS's effectiveness in managing high-dimensional food data. The close alignment between Standard Error of Calibration (SEC) and Standard Error of Prediction (SEP) suggests minimal overfitting, corroborated by Burns and Ciurczak (2007).

Low bias values further confirm accuracy in predictions as reported by Martens and Næs (1992). The RPD values, 2.9713, for cassava and 3.1759 for roasted maize flour suggest good predictive performance, aligning with Williams et al. (2019) criteria for screening purposes. Additionally, the Ratio of Error Range (RER) values support the model's effectiveness in discriminating between different levels of adulteration, consistent with findings by Nevado (2021). Previous studies further validate the PLS model's capability in detecting adulteration in complex food matrices, reinforcing the reliability and applicability of the model (Beć et al., 2022).

The results obtained for the PLS and Support Vector Machine Regression (SVMR) models applied to groundnut paste adulterated with cassava flour and roasted maize flour using mean centring (MC) preprocessing techniques reveal distinct performances. For the PLS model, the R^2 values indicate that it explains a substantial amount of variance in the training sets (0.8578 for cassava and 0.9300 for roasted maize flour) and slightly less in the testing sets, particularly for cassava flour (0.8239), reflecting moderate predictive accuracy. The SEC and SEP values are relatively close, suggesting consistent model performance, though the PLS model shows lower accuracy with cassava flour, as indicated by the lower RPD (2.4121) and RER (7.7781) values. These metrics are consistent with findings by Burns and Ciurczak (2007), who note that RPD values between 2.0 and 3.0 indicate moderate predictive ability suitable for screening purposes. Additionally, the SVMR model exhibits superior performance, with very high R^2 values for both training (0.9751 and 0.9753) and testing (0.9798 for roasted maize flour) datasets, suggesting exceptional predictive accuracy. The SEC and SEP values

are significantly lower compared to PLS, particularly for cassava flour (6.0924 and 5.6338), indicating better fit and generalization. The SVMR model also shows low bias and high RPD (5.5044 for cassava flour) and RER (17.7500), which align with Williams et al. (2019) standards for excellent model performance, typically seen in more advanced models like SVMR. According to Vapnik and Vapnik (1998), SVMR's capacity to handle non-linear relationships between variables may explain its superior performance over PLS, especially in complex food matrices like groundnut paste. Overall, these results highlight the effectiveness of SVMR in detecting and quantifying adulteration in groundnut paste, offering a more reliable alternative to PLS, especially when using MC preprocessing.

PLS and SPA-PLS models applied to groundnut paste adulterated with cassava flour and roasted maize flour, using Multiplicative Scatter Correction (MSC) preprocessing, highlight different levels of model performance. The PLS model shows strong predictive capabilities, with R^2 values of 0.8623 for cassava flour and 0.8983 for roasted maize flour in the training phase, indicating that it explains a substantial portion of the variance in the data. The testing phase R^2 values (0.8578 for cassava and 0.9310 for roasted maize flour) confirm the model's reliability, especially for roasted maize flour, where the Standard Error of Prediction (SEP) is notably lower at 8.0510. The Ratio of Performance to Deviation (RPD) for roasted maize flour (3.8518) suggests that the PLS model is highly suitable for accurate predictions, as supported by Williams et al. (2019), who states that RPD values above 3.0 indicate excellent model performance. The Ratio of Error Range (RER) values further support this, with roasted maize flour showing a high RER of 12.4208,

indicating the model's strong discriminative power. On the other hand, the SPA-PLS model demonstrates lower performance compared to the standard PLS model. The R^2 values for SPA-PLS are lower, particularly in the testing phase, with 0.7384 for cassava flour and 0.7175 for roasted maize flour. This suggests that the SPA-PLS model captures less variance and may be less effective in predicting adulteration levels. The higher SEP values for SPA-PLS (15.6706 for cassava flour and 16.2849 for roasted maize flour) further indicate a less accurate model, and the lower RPD and RER values confirm its reduced predictive power. Pandiselvam et al. (2022) reported that SPA-PLS can be beneficial in reducing model complexity and overfitting by selecting relevant variables, it may not always lead to better predictive performance compared to standard PLS, particularly when the data's underlying structure is complex, as in this case with groundnut paste adulteration. These results emphasize the superiority of the PLS model over SPA-PLS in this context, particularly when using MSC preprocessing, making PLS the preferred method for accurate adulteration detection in groundnut paste.

The results for the PLS and SPA-PLS models applied to groundnut paste adulterated with cassava flour and roasted maize flour, using Standard Normal Variate (SNV) preprocessing, show strong model performance, particularly for the PLS model. The PLS model demonstrates high R^2 values in both the training and testing phases, with cassava flour showing R^2 values of 0.8852 (training) and 0.8894 (testing), and roasted maize flour showing even higher values at 0.9278 (training) and 0.9565 (testing). These results indicate that the PLS model effectively captures the variance in the data, especially for roasted maize flour, where the Standard Error of Prediction (SEP) is notably

low at 6.3882. The high Ratio of Performance to Deviation (RPD) for roasted maize flour (4.8544) suggests excellent predictive accuracy, aligning with Williams et al., (2019), criteria where RPD values above 3.0 are considered strong for predictive models. The Ratio of Error Range (RER) for roasted maize flour (15.6540) further confirms the model's high discriminative power, making the PLS model particularly effective in detecting and quantifying adulteration. In comparison, the SPA-PLS model, while still effective, shows slightly reduced performance. For cassava flour, the R^2 values are 0.8492 (training) and 0.8894 (testing), with a higher Standard Error of Calibration (SEC) and SEP than the PLS model, indicating that SPA-PLS may not capture the data's variance as effectively. However, for roasted maize flour, the SPA-PLS model matches the PLS model in testing phase R^2 (0.9565) and SEP (6.3882), demonstrating that SPA-PLS can perform comparably to PLS under certain conditions. According to Wang et al.,(2022), SPA-PLS can reduce the risk of over fitting by selecting fewer variables, its performance is context-dependent and may not always surpass that of standard PLS, particularly in complex food matrices like groundnut paste. The results suggest that while SPA-PLS can be a useful tool, the PLS model with SNV preprocessing remains more reliable, especially for roasted maize flour adulteration detection, due to its consistently higher RPD and RER values.

The PLS and SPA-PLS models applied to groundnut paste adulterated with cassava flour and roasted maize flour, using First Derivative (FD) preprocessing, reveal nuanced differences in model performance. The PLS model demonstrates strong predictive capabilities with R^2 values of 0.9265 for cassava flour and 0.9390 for roasted maize flour in the training phase.

However, the testing phase shows a slight decrease in predictive power for cassava flour (R^2 = 0.8638) compared to roasted maize flour (R^2 = 0.9460). The Standard Error of Prediction (SEP) for cassava flour is higher at 11.3057, indicating more variability in the predictions compared to roasted maize flour, where the SEP is lower at 7.1183. The RPD value for roasted maize flour (4.3565) suggests strong predictive accuracy, aligning with Williams et al. (2019), standards for excellent model performance where RPD values above 3.0 are considered indicative of high predictive power. The Ratio of Error Range (RER) also supports this, with roasted maize flour showing a high RER of 14.0483, confirming the model's ability to distinguish between different levels of adulteration effectively (Esbensen & Romañach, 2021; Williams et al., 2019). In comparison, the SPA-PLS model shows even better performance, particularly in the testing phase, with R^2 values of 0.9601 for cassava flour and 0.9603 for roasted maize flour. This indicates that the SPA-PLS model is highly effective at capturing the variance in the data, with lower SEP values (6.1209 for cassava flour and 6.1043 for roasted maize flour) suggesting more accurate predictions. The RPD values for SPA-PLS (5.0663 for cassava flour and 5.0802 for roasted maize flour) indicate excellent predictive ability, surpassing the performance of the standard PLS model. Wang et al. (2022), note that SPA-PLS, by selecting a smaller number of relevant variables, can enhance model accuracy and reduce over fitting, particularly in complex datasets like those involving food adulteration. The higher RER values for SPA-PLS (16.3373 for cassava flour and 16.3819 for roasted maize flour) further confirm its superior discriminative power, making it the preferred method for detecting and quantifying adulteration in groundnut

paste when using FD preprocessing (Burns & Ciurczak, 2007; Wang et al., 2022).

The results from the PLS and SPA-PLS models applied to groundnut paste adulterated with cassava flour and roasted maize flour, using Second Derivative preprocessing, demonstrate distinct variations in predictive performance. The PLS model shows robust predictive capabilities with R^2 values of 0.9302 for cassava flour and 0.9570 for roasted maize flour in the training phase. However, during the testing phase, the R^2 values slightly decrease to 0.9193 for cassava flour and 0.9780 for roasted maize flour. The Standard Error of Prediction (SEP) is 8.7055 for cassava flour and a notably lower 4.5455 for roasted maize flour, indicating more precise predictions for the latter. The RPD values further support this, with roasted maize flour showing an impressive 6.8223, indicating very strong predictive power, consistent with the findings of Williams et al. (2019), who suggest that RPD values above 3.0 denote excellent model performance. Additionally, the Ratio of Error Range (RER) for roasted maize flour is particularly high at 21.9996, underscoring the model's exceptional ability to differentiate between varying levels of adulteration (Esbensen & Romañach, 2021). The SPA-PLS model also demonstrates strong performance, with R^2 values of 0.9307 for cassava flour and 0.9160 for roasted maize flour during testing. The SEP values are 8.0642 for cassava flour and 8.8780 for roasted maize flour, indicating reliable predictions with some variance. The RPD values for cassava flour (3.8455) and roasted maize flour (3.4930) suggest good predictive accuracy, though slightly lower than that of the PLS model. Also, Wang et al. (2022), emphasize that SPA-PLS, through the selection of a more focused set of

relevant variables, can achieve high model accuracy while reducing the risk of over fitting, particularly in complex mixtures such as those found in food adulteration studies. The RER values for SPA-PLS (12.4004 for cassava flour and 11.2638 for roasted maize flour) confirm the model's effective discriminative power, though slightly less pronounced than the PLS model, particularly for roasted maize flour (Burns & Ciurczak, 2007).

The PCA score plots presented in Figure 4.18 offer significant insights into the differentiation of pure groundnut paste samples from those adulterated with cassava flour and roasted maize flour. In both figures, the score plots on the first principal component (PC1) and second principal component (PC2) axes account for 99.04% and 0.7032% of the total variance, respectively. This high percentage of explained variance indicates that the PCA model is highly effective in capturing the differences between the sample types. PCA is well-established as a multivariate statistical tool for reducing dimensionality while retaining the most important variability in the data, making it particularly useful in food quality analysis (Jolliffe & Cadima, 2016). In Figure 27(I), which represents groundnut paste adulterated with cassava flour, there is a clear distinction between pure and adulterated samples. The pure groundnut pastes samples, represented by blue circles, cluster distinctly on the left side of the plot, while the adulterated samples, represented by red circles, are mostly grouped on the right. This separation along PC1 indicates that cassava flour adulteration significantly affects the spectral characteristics captured by the PCA model. The clustering pattern suggests that the pure and adulterated samples have distinct properties that can be reliably distinguished using PCA, aligning with findings in similar studies on food adulteration detection

(Medina Escudero et al., 2019). Similarly, in Figure 27(II), which depicts groundnut paste adulterated with roasted maize flour, a comparable separation is observed. The pure samples again cluster separately from the adulterated ones, with clear demarcation along the PC1 axis. The presence of the adulterated samples primarily on the right side of the plot further emphasizes the effectiveness of PCA in identifying adulteration in groundnut paste, even when different adulterants like roasted maize flour are used. This is consistent with prior research that has demonstrated the capability of PCA to distinguish between food samples with different levels of purity and adulteration (Biancolillo et al., 2020).

CHAPTER FIVE

OVERVIEW, CONCLUSION AND RECOMMENDATION

Overview

The research sought to validate the safety and quality of commercial groundnut paste sold on the Ghanaian market and the feasibility of using handheld NIR to detect the presence or absence of foreign materials. Commercial groundnut paste samples were purchased from some major markets in the Central region for quality and fungus determination. Groundnut was purchased and processed into groundnut paste. This was adulterated with cassava flour and roasted maize flour at different concentrations to assess the feasibility of the handheld NIR spectrometer to detect adulteration. Nevertheless, the possibility of using a handheld NIR spectrometer coupled with chemometric analysis to detect adulteration of groundnut paste with cassava flour or roasted maize flour has been demonstrated in this study

Summary

The study reveals the results obtained from the quality assessment of commercial groundnut paste on the Ghanaian market showed that some of the commercial groundnut paste samples analyzed were not within the Codex Alimentarius standard. The moisture content, the acid value, and the peroxide value met the Codex Alimentarius standard quality indicators (3.2%, 4.0% and 10mq respectively). However, all samples tested positive for fungi infestation. This could be attributed to poor processing, storage and hygienic conditions on the market.

The study on the feasibility of using a handheld NIR spectrometer to detect adulterated groundnut paste with either cassava flour or roasted maize

flour showed a PCA of 99.04% for both cassava flour and roasted maize flour adulterants respectively. That is, the handheld NIR spectrometer coupled with chemometric analysis was able to discriminate between the pure groundnut paste samples from the adulterated samples.

Conclusions

This study successfully assessed the safety and quality of groundnut paste in the Central Region of Ghana using both conventional wet chemistry methods and a novel approach handheld portable Near-Infrared (NIR) spectroscopy combined with chemometrics. Through comprehensive physicochemical and microbial analyses, the study identified variances in moisture content, protein levels, fat content, peroxide values, and free fatty acid concentrations across groundnut paste samples. Notably, the fungal contamination observed ranged between 1.60 – 2.48 $\log_{10}$ CFU/g, which, while relatively low, highlights the potential for microbial hazards.

The application of handheld NIR spectroscopy proved effective in real-time detection of adulterants such as cassava flour and roasted maize flour in groundnut paste, achieving high predictive accuracy (R^2 values of 0.9751 and 0.9753 for cassava and maize flour, respectively). This approach offers a rapid, non-destructive, and eco-friendly alternative to conventional laboratory methods, addressing the significant gap in the availability of cost-effective and efficient on-site adulteration detection techniques.

By integrating machine learning algorithms like Support Vector Machine (SVM) and chemometric tools such as Principal Component Analysis (PCA), the study demonstrated the potential of NIR spectroscopy as a powerful tool for food quality control in resource-limited settings. This

research fills a critical gap in the literature, where prior studies predominantly focused on complex, laboratory-bound methods that are often inaccessible to local producers and regulatory bodies in Ghana.

Recommendations

1. Groundnut paste producers should implement standardized post-harvest drying and storage practices to control moisture content, reduce microbial contamination, and prevent lipid oxidation, ensuring consistent protein and fat levels across batches.
2. Producers should adopt strict hygienic practices, including regular equipment sanitation and proper handling during processing and packaging, while regulatory bodies should conduct routine microbial testing to ensure compliance with national food safety standards.
3. Stakeholders, including food safety regulators and groundnut paste manufacturers, should incorporate handheld Near-Infrared (NIR) spectroscopy as a cost-effective, rapid, and non-destructive method for real-time adulteration detection.
4. Policymakers should consider incorporating NIR spectroscopy into existing food monitoring frameworks to improve the traceability, authenticity, and overall safety of groundnut paste sold in Ghanaian markets.
5. Future studies should explore the potential of NIR spectroscopy to detect a broader range of contaminants, such as aflatoxins, and expand its application to other food products for comprehensive food safety management.

REFERENCES

Abimbola, O. F., Okpara, M. O., Njikam, M. J., & Elejo, A. C. (2023). Artificial Intelligence in Food Fraud and Traceability. *Sensing and Artificial Intelligence Solutions for Food Manufacturing*, 117–130.

Adazebra, I. A. (2019). *Evaluation of mutant genotypes of groundnut (arachis hypogaea l) for improved agronomic traits and stability (Doctoral dissertation).*

Adebayo, S. E., Orhevba, B. A., Adeoye, P. A., Musa, J. J., & Fase, O. J. (2012). *Solvent extraction and characterization of oil from African Star Apple (Chysophyllumalbidum).* http://repository.futminna.edu.ng :8080/jspui/handle/123456789/1851

Adrian, J. (2019). The maillard reaction. In *Handbook of nutritive value of processed food* (pp. 529–608). CRC Press. https://www.taylorfrancis.com/chapters/edit/10.1201/9780429290527-22/maillard-reaction-adrian

Alimentarius, C. (1999). Codex standard for named vegetable oils. *Codex Stan*, *210*, 1–13.

Anita, G., & Neetu, S. (2013). Hazards of new technology in promoting food adulteration. *IOSR Journal of Environmental Science, Toxicology and Food Technology*, *5*(1), 08–10.

Aykas, D. P., & Menevseoglu, A. (2021). A rapid method to detect green pea and peanut adulteration in pistachio by using portable FT-MIR and FT-NIR spectroscopy combined with chemometrics. *Food Control*, *121*, 107670.

Ayza, A., & Yilma, Z. (2014). Patterns of milk and milk product adulteration in Boditti town and its surrounding South Ethiopia. *J Agric Sci*, *4*(10), 512–516.

Bakhiet, S. E. A., & Musa, A. A. A. (2011). Survey and determination of aflatoxin levels in stored peanuts in Sudan. *Jordan Journal of Biological Sciences*, *4*(1), 13–20.

Bansal, S., Singh, A., Mangal, M., Mangal, A. K., & Kumar, S. (2017). Food adulteration: Sources, health risks, and detection methods. *Critical Reviews in Food Science and Nutrition*, *57*(6), 1174–1189.

Bao, L., Trucksess, M. W., & White, K. D. (2010). Determination of aflatoxins B1, B2, G1, and G2 in olive oil, peanut oil, and sesame oil. *Journal of AOAC International*, *93*(3), 936–942.

Beć, K. B., Grabska, J., & Huck, C. W. (2022). Miniaturized near-infrared spectroscopy in current analytical chemistry: From natural products to forensics. In *Molecular and Laser Spectroscopy* (pp. 141–188). Elsevier. https://www.sciencedirect.com/science/article/pii/B9780323912495000090

Bevilacqua, M., Bucci, R., Materazzi, S., & Marini, F. (2013). Application of near-infrared (NIR) spectroscopy coupled to chemometrics for dried egg-pasta characterization and egg content quantification. *Food Chemistry*, *140*(4), 726–734.

Biancolillo, A., Marini, F., Ruckebusch, C., & Vitale, R. (2020). Chemometric strategies for spectroscopy-based food authentication. *Applied Sciences*, *10*(18), 6544.

Bimpong, D., Adofowaa, L. A., Agyeman, A., Boakye, A., Oduro, I. N., Otoo, E. W., & Zaukuu, J.-L. Z. (2023). Authenticating peanut butter and yoghurt in the Kumasi Metropolis of Ghana using near-infrared spectroscopy. *Progress in Agricultural Engineering Sciences*, *19*(1), 69–81.

Blutinger, J. D. (2022). *Digital Cuisine: Food Printing and Laser Cooking*. Columbia University. https://search.proquest.com/openview/c8d1af89c389fee10d581df0d4cdd6c7/1?pq-origsite=gscholar&cbl=18750&diss=y

Boadu, V. G., Teye, E., Amuah, C. L., Lamptey, F. P., & Sam-Amoah, L. K. (2023). Portable NIR Spectroscopic Application for Coffee Integrity and Detection of Adulteration with Coffee Husk. *Processes*, *11*(4), 1140.

Boli, Z. A., Kouame, K. A., Bouatenin, K. M. J. P., Koffi-Nevry, R., & Dje, K. M. (2017). Technical Sheet of Physicochemical and Mycological Characteristics of the Groundnut Paste Sold in Retail Markets of Abidjan Town (cote d'ivoire). *International Journal of Pharmaceutical, Chemical & Biological Sciences*, *7*(4), 327–334.

Bottemiller, H. (2011). Chinese Authorities Seize Melamine-tainted Dairy. *Food Safety News*, 26–27.

Burnett, S. L., Gehm, E. R., Weissinger, W. R., & Beuchat, L. R. (2000). Survival of Salmonella in peanut butter and peanut butter spread. *Journal of Applied Microbiology*, *89*(3), 472–477.

Burns, D. A., & Ciurczak, E. W. (2007). *Handbook of near-infrared analysis*. CRC press.

Cen, H., & He, Y. (2007). Theory and application of near-infrared reflectance spectroscopy in determination of food quality. *Trends in Food Science & Technology*, *18*(2), 72–83.

Chakuri, D. (2018). Technical efficiency analysis of groundnut production in Ghana: A Bayesian approach. *University of Ghana. URL: Http:// Ugspace. Ug. Edu. Gh/Handle/123456789/29130*.

Chijoriga, Z. (2017). *Quality and safety of peanut butter processed by small and medium enterprises in Dar es Salaam region* [PhD Thesis]. Sokoine University of Agriculture.

Chinemerem Henry Ugo, Paul Eze Eme, Perpetua Ngozi Eze, Henry Asusheyi Obajaja, & Afoma Emmanuela Omeili. (2024). Chemical assessment of the quality of palm oil produced and sold in major markets in the Orlu zone in Imo state, Nigeria. *World Journal of Advanced Research and Reviews*, *21*(2), 1025–1033. https://doi.org/10.30574/wjarr.2024.21.2.0529

Choudhary, A., Gupta, N., Hameed, F., & Choton, S. (2020). An overview of food adulteration: Concept, sources, impact, challenges and detection. *International Journal of Chemical Studies*, *8*(1), 2564–2573.

Cohen, N. J., Deeds, J. R., Wong, E. S., Hanner, R. H., Yancy, H. F., White, K. D., Thompson, T. M., Wahl, I., Pham, T. D., & Guichard, F. M. (2009). Public health response to puffer fish (tetrodotoxin) poisoning from mislabeled product. *Journal of Food Protection*, *72*(4), 810–817.

Countryman, S., Huq, S., & Mathews, T. (2009). Rapid high-resolution analysis of aflatoxin extracts from peanut butter using Kinetex core-shell technology and strata. *SPE, CAPhenomenex Inc., USA*.

Crocombe, R. A. (2018). Portable spectroscopy. *Applied Spectroscopy*, *72*(12), 1701–1751.

Czarnecki, M. A., Morisawa, Y., Futami, Y., & Ozaki, Y. (2015). Advances in molecular structure and interaction studies using near-infrared spectroscopy. *Chemical Reviews*, *115*(18), 9707–9744.

Dhanya, K., Syamkumar, S., & Sasikumar, B. (2009). Development and application of SCAR marker for the detection of papaya seed adulteration in traded black pepper powder. *Food Biotechnology*, *23*(2), 97–106.

Dhiman, B., & Singh, M. (2003). Molecular detection of cashew husk (Anacardium occidentale) adulteration in market samples of dry tea (Camellia sinensis). *Planta Medica*, *69*(09), 882–884.

Diao, Y.Z., Zhang, C., Liu, F., Wang, W.Z., Liu, L., Cai, L., & Liu, X.L. (2017). Colletotrichum species causing anthracnose disease of chilli in China. *Persoonia-Molecular Phylogeny and Evolution of Fungi*, *38*(1), 20–37.

Dorley, O. S. (2015). *Studies of Aspergillus flavus and Aflatoxin contamination of groundnut (arachis hypogaea l) from six markets in the central region, Ghana.* [PhD Thesis, University of Cape Coast]. https://ir.ucc.edu.gh/xmlui/handle/123456789/2541

Dos Santos, C. A. T., Lopo, M., Páscoa, R. N., & Lopes, J. A. (2013). A review of the applications of portable near-infrared spectrometers in the agro-food industry. *Applied Spectroscopy*, *67*(11), 1215–1233.

Downey, G. (2016). *Advances in food authenticity testing*. Woodhead Publishing.

Elliott, C. (2014). *Elliott Review into the integrity and assurance of food supply networks report: A national food crime prevention framework*.

Elmi, M. (2004). Food safety: Current situation, unaddressed issues and the emerging priorities. *EMHJ-Eastern Mediterranean Health Journal, 10 (6), 794-800, 2004*.

El-Rawas, A., Hvizdzak, A., Davenport, M., Beamer, S., Jaczynski, J., & Matak, K. (2012). Effect of electron beam irradiation on quality indicators of peanut butter over a storage period. *Food Chemistry*, *133*(1), 212–219.

Epelboin, L., Pérignon, A., Hossen, V., Vincent, R., Krys, S., & Caumes, E. (2014). Two clusters of ciguatera fish poisoning in Paris, France, related to tropical fish imported from the French Caribbean by travellers. *Journal of Travel Medicine*, *21*(6), 397–402.

Esbensen, K. H., & Romañach, R. J. (2021). 19 A Framework for Representative Sampling for NIR Analysis–Theory of Sampling (TOS). *Handbook of Near-Infrared Analysis*, 415.

Essei, E., & Amadi, C. (2009). Physicochemical characterisation of butternut (Juglans cinerea) oil. *Global Journal of Pure and Applied Sciences*, *15*(3–4). https://www.ajol.info/index.php/gjpas/article/view/48550

Essuman, E. K., Teye, E., Dadzie, R. G., & Sam-Amoah, L. K. (2022). Consumers' knowledge of food adulteration and commonly used methods of detection. *Journal of Food Quality*, *2022*, 1–10.

Fandohan, P., Hell, K., & Marasas, W. F. O. (2008). Food processing to reduce mycotoxins in Africa. In J. F. Leslie, R. Bandyopadhyay, & A. Visconti (Eds.), *Mycotoxins: Detection methods, management, public*

health and agricultural trade (1st ed., pp. 309–316). CABI. https://doi.org/10.1079/9781845930820.0309

Faraz, A., Lateef, M., Mustafa, M., Akhtar, P., Yaqoob, M., & Rehman, S. (2013). *Detection of adulteration, chemical composition and hygienic status of milk supplied to various canteens of educational institutes and public places in Faisalabad.*

Friedman, M. (2015). Acrylamide: Inhibition of formation in processed food and mitigation of toxicity in cells, animals, and humans. *Food & Function*, *6*(6), 1752–1772.

Girei, A., Dauna, Y., & Dire, B. (2013). An economic analysis of groundnut (Arachis hypogea) production in Hong local government area of Adamawa State, Nigeria. *Journal of Agricultural and Crop Research*, *1*(6), 84–89.

Global Food Safety Initiative. (2014). *GFSI position on mitigating the public health risk of food fraud, global food safety initiative, consumer goods forum*.

González Martín, M. I., Wells Moncada, G., Fischer, S., & Escuredo, O. (2014). Chemical characteristics and mineral composition of quinoa by near-infrared spectroscopy. *Journal of the Science of Food and Agriculture*, *94*(5), 876–881.

González-Martín, M. I., Moncada, G. W., González-Pérez, C., San Martín, N. Z., López-González, F., Ortega, I. L., & Hernández-Hierro, J.M. (2014). Chilean flour and wheat grain: Tracing their origin using near-infrared spectroscopy and chemometrics. *Food Chemistry*, *145*, 802–806.

Gossner, C. M.E., Schlundt, J., Ben Embarek, P., Hird, S., Lo-Fo-Wong, D., Beltran, J. J. O., Teoh, K. N., & Tritscher, A. (2009). The melamine incident: Implications for international food and feed safety. *Environmental Health Perspectives*, *117*(12), 1803–1808.

Guteta, A. (2017). *Characterization of scavenging and intensive poultry production and marketing system at Lume woreda, East Shoa zone*.

Guy-Rolande, G. O. N., Arthur, Z. C., Philippe, E. K., Athanase, K. K., Clément, K. K., & Ibrahim, K. (2024). Evaluation of Some Microbiological and Physicochemical Parameters of Peanut Pastes Collected in Some Public Markets in the City of Daloa, Côte d'Ivoire. *Journal of Advances in Biology & Biotechnology*, *27*(4), 50–58.

Honfo, F., Hell, K., Akissoé, N., Coulibaly, O., Fandohan, P., & Hounhouigan, J. (2011). Effect of storage conditions on microbiological and physicochemical quality of shea butter. *Journal of Food Science and Technology*, *48*(3), 274–279. https://doi.org/10.1007/s13197-010-0150-x

Humans, I. W. G. on the E. of C. R. too, Cancer, I. A. for R. on, & Organization, W. H. (2002). *Some traditional herbal medicines, some mycotoxins, naphthalene and styrene*. World Health Organization. https://books.google.com/books?hl=en&lr=&id=iUXBe9cYzW8C&oi=fnd&pg=PP2&dq=IARC+Monographs+(2002).+Some+traditional+herbal+medicines,+Some+mycotoxins,++naphthalene+and+styrene.+%5Bhttp://monographs.iarc.fr/ENG/Monogra+phs/vol82++/mono82-7A.pdf%5D+site+visited+on+3/8/2016.&ots=1phzTvd18Z&sig=rpjJytyfQjm0hvVyRZkOpv3C_Ps

Hurley, I. P., Elyse Ireland, H., Coleman, R. C., & Williams, J. H. (2004). Application of immunological methods for the detection of species adulteration in dairy products. *International Journal of Food Science & Technology*, *39*(8), 873–878.

Ibrahim, M., Florkowski, W. J., & Kolavalli, S. (2012). *Determinants of Farmer Adoption of Improved Peanut Varieties and their Impact on Farm Income: Evidence from Northern Ghana.*

Islam, M. F., Uddin, M. N., Rana, A. A., & Mainul, M. (2018). Development of a chemometric method for the analysis of Sudan III-IV dye adulteration in chilli powder using UV-visible spectroscopy data. *Journal of Scientific and Innovative Research*, *7*(2), 30–35.

Joardder, M. U. H., Mourshed, M., & Hasan Masud, M. (2019). *State of Bound Water: Measurement and Significance in Food Processing*. Springer International Publishing. https://doi.org/10.1007/978-3-319-99888-6

Johnson, R. (2014). *Food fraud and economically motivated adulteration of food and food ingredients*.

Joint, F. (2001). Codex Alimentarius: Food hygiene basic texts. In *Codex Alimentarius: Food hygiene basic texts* (pp. 70–70).

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202

Kamika, I., & Takoy, L. L. (2011). Natural occurrence of Aflatoxin B1 in peanuts collected from Kinshasa, Democratic Republic of Congo. *Food Control*, *22*(11), 1760–1764.

Kandala, C. V. K., Butts, C. L., & Lamb, M. C. (2008). Moisture content determination for in-shell peanuts with a low-cost impedance analyzer and capacitor sensor. *Transactions of the ASABE*, *51*(4), 1377–1381.

Khatri, Y., & Collins, R. (2007). Impact and status of HACCP in the Australian meat industry. *British Food Journal*, *109*(5), 343–354.

Lakshmi, V., & Pradesh, A. (2012). Food adulteration. *International Journal of Science Inventions Today*, *1*(2), 106–113.

Lee, C. M., & Resurreccion, A. V. A. (2006). Predicting sensory attribute intensities and consumer acceptance of stored roasted peanuts using instrumental measurements. *Journal of Food Quality*, *29*(4), 319–338. https://doi.org/10.1111/j.1745-4557.2006.00076.x

Leffler, T. P., Moser, C. R., McManus, B. J., Urh, J. J., Keeton, J. T., Claflin, A., & Collaborators: Adkins K Claflin A Davis C Elliot J Goin P Horn C Humphries J Ketteler K Perez P Steiner G. (2008). Determination of moisture and fat in meats by microwave and nuclear magnetic resonance analysis: Collaborative study. *Journal of AOAC International*, *91*(4), 802–810.

Li, H., Fan, Y., Li, J., Tang, L., Hu, J., & Deng, Z. (2013). Evaluating and Predicting the Oxidative Stability of Vegetable Oils with Different Fatty Acid Compositions. *Journal of Food Science*, *78*(4). https://doi.org/10.1111/1750-3841.12089

Li, Y. (2008). Types and proportions of adulterations in six kinds of condiments. *China Condiment*, *8*, 81–83.

MacArthur, R. L., Teye, E., & Darkwa, S. (2020). Predicting adulteration of Palm oil with Sudan IV dye using shortwave handheld spectroscopy and comparative analysis of models. *Vibrational Spectroscopy*, *110*, 103129.

Mahfoud, F., Assaf, J. C., Elias, R., Debs, E., & Louka, N. (2023). Defatting and Defatted Peanuts: A Critical Review on Methods of Oil Extraction and Consideration of Solid Matrix as a By-Product or Intended Target. *Processes*, *11*(8), 2512.

Manning, L., & Soon, J. M. (2016). Food safety, food fraud, and food defence: A fast evolving literature. *Journal of Food Science*, *81*(4), R823–R834.

Martens, H., & Næs, T. (1992). *Multivariate calibration*. John Wiley & Sons. https://books.google.com/books?hl=en&lr=&id=6lVcUeVDg9IC&oi=fnd&pg=PR13&dq=N%C3%A6s,+T.,+et+al.+(2002).+Multivariate+Calibration.+John+Wiley+%26+Sons.+This+book+provides+insights+into+calibration+methods+and+the+significance+of+bias+in+predictive+models.&ots=wt59grYzLv&sig=N4i8Z_l5k9dXiSVcbAz4wEFEiT8

Masaka, V., Ndlovu, N., Tshalibe, R., Mhande, T., & Jombo, T. (2022). Prevalence of Aflatoxin Contamination in Peanuts and Peanut Butter from an Informal Market, Harare, Zimbabwe. *International Journal of Food Science*, *2022*.

Masih, L. P., Sonkar, C., Singh, S., & Chauhan, R. (2017). Physico-chemical properties of biscuits are influenced by different ratios of hydrogenated fat (vanaspati) and peanut butter. *Int. J. Curr. Microbiol. App. Sci*, *6*(12), 1804–1811.

McDaniel, K. A., White, B. L., Dean, L. L., Sanders, T. H., & Davis, J. P. (2012). Compositional and Mechanical Properties of Peanuts Roasted to Equivalent Colors using Different Time/Temperature Combinations. *Journal of Food Science*, *77*(12). https://doi.org/10.1111/j.1750-3841.2012.02979.x

Medina Escudero, S., Perestrelo, R., Silva, P., Pereira, J. A., & Câmara, J. S. (2019). *Current trends and recent advances in food authenticity technologies and chemometric approaches*. https://digital.csic.es/handle/10261/342459

Menevseoglu, A., Aykas, D. P., & Adal, E. (2021). Non-targeted approach to detect green pea and peanut adulteration in pistachio by using portable FT-IR, and UV–Vis spectroscopy. *Journal of Food Measurement and Characterization*, *15*(2), 1075–1082. https://doi.org/10.1007/s11694-020-00710-y

Meng, T., Florkowski, W. J., Klepacka, A. M., Sarpong, D. B., Resurreccion, A. V., Chinnan, M. S., & Ekielski, A. (2018). Preferences for groundnut products among urban residents in Ghana. *Journal of the Science of Food and Agriculture*, *98*(2), 817–824.

Mergenthaler, M., Weinberger, K., & Qaim, M. (2009). The food system transformation in developing countries: A disaggregate demand analysis for fruits and vegetables in Vietnam. *Food Policy*, *34*(5), 426–436.

Moustier, P., Tam, P. T. G., Anh, D. T., Binh, V. T., & Loc, N. T. T. (2010). The role of farmer organizations in supplying supermarkets with quality food in Vietnam. *Food Policy*, *35*(1), 69–78.

Mubaiwa, J., Fogliano, V., Chidewe, C., & Linnemann, A. R. (2018). Bambara groundnut (Vigna subterranean (L.) Verdc.) flour: A functional ingredient to favour the use of an unexploited sustainable protein source. *PloS One*, *13*(10), e0205776.

Mustorp, S., Engdahl-Axelsson, C., Svensson, U., & Holck, A. (2008). Detection of celery (Apium graveolens), mustard (Sinapis alba, Brassica juncea, Brassica nigra) and sesame (Sesamum indicum) in food by real-time PCR. *European Food Research and Technology*, *226*(4), 771–778.

Mutegi, C. K., Ngugi, H. K., Hendriks, S. L., & Jones, R. B. (2009). Prevalence and factors associated with aflatoxin contamination of peanuts from Western Kenya. *International Journal of Food Microbiology*, *130*(1), 27–34.

Mutegi, C. K., Ngugi, H. K., Hendriks, S. L., & Jones, R. B. (2012). Factors associated with the incidence of *Aspergillus* section *Flavi* and aflatoxin contamination of peanuts in the Busia and Homa Bay districts of western Kenya. *Plant Pathology*, *61*(6), 1143–1153. https://doi.org/10.1111/j.1365-3059.2012.02597.x

Muttagi, G. C., Joshi, N., Shadakshari, Y. G., & Chandru, R. (2014). Storage stability of value-added products from sunflower kernels. *Journal of Food Science and Technology*, *51*(9), 1806–1816. https://doi.org/10.1007/s13197-014-1261-6

Narayan, D. (2014). Food Adulteration: Types, worldwide laws and futures. *Health Care*, *1*, 2–8.

Nevado, J. M. C. (2021). *TITULO: From at-line analysis to on-site control in the Iberian pig industry using Near Infrared Spectroscopy sensors* [PhD Thesis, Universidad de Sevilla]. https://core.ac.uk/download/pdf/459229604.pdf

Ngando-Ebongue, G. F., Ajambang, W. N., Koona, P., Firman, B. L., & Arondel, V. (2012). Oil Palm. In S. K. Gupta (Ed.), *Technological Innovations in Major World Oil Crops, Volume 1* (pp. 165–200). Springer New York. https://doi.org/10.1007/978-1-4614-0356-2_7

Nguz, K. (2007). Assessing food safety system in sub-Saharan countries: An overview of key issues. *Food Control*, *18*(2), 131–134.

Nigam, S. N., Waliyar, F., Aruna, R., Reddy, S. V., Kumar, P. L., Craufurd, P. Q., Diallo, A. T., Ntare, B. R., & Upadhyaya, H. D. (2009). Breeding peanut for resistance to aflatoxin contamination at ICRISAT. *Peanut Science*, *36*(1), 42–49.

Nizam, A. F. A., & Mahmud, M. S. (2021). Food quality assurance of crude palm oil: A review on toxic ester feedstock. *OCL*, *28*, 23.

Nkansah, M. A., Adrewie, D., Darko, G., & Dodd, M. (2021a). Potential elemental exposure and health risks associated with the consumption of groundnut paste processed with local milling machines within the Kumasi metropolis. *Scientific African*, *13*, e00967.

Nkansah, M. A., Adrewie, D., Darko, G., & Dodd, M. (2021b). Potential elemental exposure and health risks associated with the consumption of groundnut paste processed with local milling machines within the Kumasi metropolis. *Scientific African*, *13*, e00967.

Okechalu, J. N., Dashen, M. M., Lar, P. M., Okechalu, B., & Gushop, T. (2011). *Microbiological quality and chemical characteristics of palm oil sold within Jos Metropolis, Plateau State, Nigeria*. https://dspace.unijos.edu.ng/jspui/handle/123456789/1040

Omari, R., Tetteh, E., Baah-Tuahene, S., Karbo, R., Adams, A., & Asante, I. (2020). *Aflatoxins and their management in Ghana: A situational analysis*.

Ortega, D. L., & Tschirley, D. L. (2017). Demand for food safety in emerging and developing countries: A research agenda for Asia and Sub-Saharan Africa. *Journal of Agribusiness in Developing and Emerging Economies*, *7*(1), 21–34.

Owusu-Adjei, E., Baah-Mintah, R., & Salifu, B. (2017). Analysis of the groundnut value chain in Ghana. *World J Agric*, *5*(3), 177–188.

Pafundo, S., Agrimonti, C., Maestri, E., & Marmiroli, N. (2007). Applicability of SCAR markers to food genomics: Olive oil traceability. *Journal of Agricultural and Food Chemistry*, *55*(15), 6052–6059.

Pandiselvam, R., Prithviraj, V., Manikantan, M., Kothakota, A., Rusu, A. V., Trif, M., & Mousavi Khaneghah, A. (2022). Recent advancements in NIR spectroscopy for assessing the quality and safety of horticultural products: A comprehensive review. *Frontiers in Nutrition*, *9*, 973457.

Payne, G. A. (2016). Mycotoxins and product safety. In *Peanuts* (pp. 347–361). Elsevier. https://www.sciencedirect.com/science/article/pii/B9781630670382000125

Pearson, D. (1976). The chemical analysis of foods. Churchill Livingstone. *New York*, 6–19.

Pérez-Marín, D. C., & Garrido-Varo, A. (2006). Near-Infrared Spectroscopy and Chemometrics in Food and Agriculture. *Encyclopedia of Analytical Chemistry: Applications, Theory and Instrumentation*, 1–39.

Pérez-Marín, D. C., Garrido-Varo, A., Guerrero-Ginel, J., & Gómez-Cabrera, A. (2004). Near-infrared reflectance spectroscopy (NIRS) for the mandatory labelling of compound feedingstuffs: Chemical composition and open-declaration. *Animal Feed Science and Technology*, *116*(3–4), 333–349.

Podolak, R., & Black, D. G. (Eds.). (2017). *Control of Salmonella and Other Bacterial Pathogens in Low Moisture Foods* (1st ed.). Wiley. https://doi.org/10.1002/9781119071051

Pu, Y., Pérez-Marín, D., O'Shea, N., & Garrido-Varo, A. (2021). Recent advances in portable and handheld NIR spectrometers and applications in milk, cheese and dairy powders. *Foods*, *10*(10), 2377.

Reardon, T., & Chen, K. (2012). *The quiet revolution in staple food value chains*.

Reardon, T., Timmer, C. P., & Minten, B. (2012). Supermarket revolution in Asia and emerging development strategies to include small farmers. *Proceedings of the National Academy of Sciences*, *109*(31), 12332–12337.

Roberts, T. A., vanSchothorst, M., Sharpe, A. N., BairdParker, A. C., Bryan, F. L., Buchanan, R. L., Busta, F. F., Doyle, M. P., Farkas, J., & Grau, F. H. (1996). The international commission on microbiological specifications for foods (ICMSF): Update. *Food Control*, *7*(2), 99–101.

Rodriguez-Saona, L. E., & Allendorf, M. E. (2011). Use of FTIR for rapid authentication and detection of adulteration of food. *Annual Review of Food Science and Technology*, *2*, 467–483.

Roiaini, M., Ardiannie, T., & Norhayati, H. (2015). Physicochemical properties of canola oil, olive oil and palm olein blends. *International Food Research Journal*, *22*(3), 1227.

Samson, R., Houbraken, J., Thrane, U., Frisvad, J., & Andersen, B. (2010). Food and indoor fungi: CBS-KNAW fungal biodiversity centre. *CBS-KNAW Fungal Biodiversity Centre, Utrecht, the Netherlands*.

Sasikumar, B., Syamkumar, S., Remya, R., & John Zachariah, T. (2004). PCR-based detection of adulteration in the market samples of turmeric powder. *Food Biotechnology*, *18*(3), 299–306.

Settaluri, V. S., Kandala, C. V. K., Puppala, N., & Sundaram, J. (2012). *Peanuts and their nutritional aspects—A review*. https://www.scirp.org/html/5-2700529_25267.htm

Shapla, U. M., Solayman, Md., Alam, N., Khalil, Md. I., & Gan, S. H. (2018). 5-Hydroxymethylfurfural (HMF) levels in honey and other food products: Effects on bees and human health. *Chemistry Central Journal*, *12*(1), 35. https://doi.org/10.1186/s13065-018-0408-3

Shelar, M., Bafna, A., Wahile, A., & Tupkari, S. (2011). *Evaluation of edible oils for Argemone mexicana seed oil adulteration.*

Shenk, J., & Westerhaus, M. (1994). The application of near-infrared reflectance spectroscopy (NIRS) to forage analysis. *Forage Quality, Evaluation, and Utilization*, 406–449.

Shibli, S., Siddique, F., Raza, S., Ahsan, Z., & Raza, I. (2019). Chemical composition and sensory analysis of peanut butter from indigenous peanut cultivars of Pakistan. *Pakistan Journal of Agricultural Research*, *32*(1), 159.

Sithole, T. R., Ma, Y.X., Qin, Z., Liu, H.M., & Wang, X.D. (2022). Influence of peanut varieties on the sensory quality of peanut butter. *Foods*, *11*(21), 3499.

Smartt, J. (2012). *The groundnut crop: A scientific basis for improvement*. Springer Science & Business Media.

Spink, J., & Moyer, D. C. (2011). Defining the public health threat of food fraud. *Journal of Food Science*, *76*(9), R157–R163.

Stiborová, M., Martínek, V., Rýdlová, H., Hodek, P., & Frei, E. (2002). Sudan I is a potential carcinogen for humans: Evidence for its metabolic activation and detoxication by human recombinant cytochrome P450 1A1 and liver microsomes. *Cancer Research*, *62*(20), 5678–5684.

Tagoe, S. M. A., Dickinson, M. J., & Apetorgbor, M. M. (2012). Factors influencing the quality of palm oil produced at the cottage industry level in Ghana. *International Food Research Journal*, *19*(1). https://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=19854668&AN=69631923&h=3Astj4gd1v9N0FUSxOhdtjRbrU%2Fnw6GB%2BMh5ptrBQ65Co5FMLCIp2KNiCnq3VKgtCSXkU6hoN4IwwJYC9lI5uQ%3D%3D&crl=c

Taphee, G., Jongur, A., Giroh, D. Y., & Jen, E. I. (2015). Analysis of profitability of groundnut production in the northern part of Taraba State, Nigeria. *International Journal of Computer Applications*, *125*(1).

Teye, E., & Amuah, C. L. (2022). Rice varietal integrity and adulteration fraud detection by chemometrics analysis of pocket-sized NIR spectra data. *Applied Food Research*, *2*(2), 100218.

Teye, E., Anyidoho, E., Agbemafle, R., Sam-Amoah, L. K., & Elliott, C. (2020). Cocoa bean and cocoa bean products quality evaluation by NIR spectroscopy and chemometrics: A review. *Infrared Physics & Technology*, *104*, 103127.

Teye, E., Elliott, C., Sam-Amoah, L. K., & Mingle, C. (2019). Rapid and nondestructive fraud detection of palm oil adulteration with Sudan dyes using portable NIR spectroscopic techniques. *Food Additives & Contaminants: Part A*, *36*(11), 1589–1596.

Teye, E., Huang, X., Lei, W., & Dai, H. (2014). Feasibility study on the use of Fourier transform near-infrared spectroscopy together with chemometrics to discriminate and quantify adulteration in cocoa beans. *Food Research International*, *55*, 288–293.

Teye, E., Huang, X., Sam-Amoah, L. K., Takrama, J., Boison, D., Botchway, F., & Kumi, F. (2015). Estimating cocoa bean parameters by FT-NIRS and chemometrics analysis. *Food Chemistry*, *176*, 403–410.

Tian, L., Zeng, Y., Zheng, X., Chiu, Y., & Liu, T. (2019). Detection of Peanut Oil Adulteration Mixed with Rapeseed Oil Using Gas Chromatography and Gas Chromatography–Ion Mobility Spectrometry. *Food Analytical Methods*, *12*(10), 2282–2292. https://doi.org/10.1007/s12161-019-01571-y

Tornincasa, P., Furlan, M., Pallavicini, A., & Graziosi, G. (2010). *Coffee species and varietal identification*.

Tortoe, C., Akonor, P. T., & Buckman, E. S. (2017). Potential uses of sweet potato-wheat composite flour in the pastry industry based on proximate composition, physicochemical, functional, and sensory properties of four pastry products. *Journal of Food Processing and Preservation*, *41*(5), e13206. https://doi.org/10.1111/jfpp.13206

Tripathi, S., & Mishra, H. N. (2011). Modeling and Optimization of Enzymatic Degradation of Aflatoxin B1 (AFB1) in Red Chili Powder Using Response Surface Methodology. *Food and Bioprocess Technology*, *4*(5), 770–780. https://doi.org/10.1007/s11947-009-0216-9

Tschirley, D., Haggblade, S., & Reardon, T. (2013). Africa's emerging food system transformation. *East Lansing: Michigan State University Global Center for Food System Innovation*.

Tsigbey, F., Brandenburg, R. L., & Clottey, V. A. (2003). Peanut production methods in northern Ghana and some disease perspectives. *World Geography of the Peanut Knowledge Base Website*, *9*, 33–38.

Unnevehr, L., & Hirschhorn, N. (2000). *Food safety issues in the developing world* (Vol. 469). World Bank Publications.

Vapnik, V. N., & Vapnik, V. (1998). *Statistical learning theory*. http://lib.ysu.am/disciplines_bk/22cca8eefb24af29d10bbc661e3a5ebf.pdf

Villa, P., & Markaki, P. (2009). Aflatoxin B1 and ochratoxin A in breakfast cereals from Athens market: Occurrence and risk assessment. *Food Control*, *20*(5), 455–461.

Wang, H.P., Chen, P., Dai, J.W., Liu, D., Li, J.Y., Xu, Y.P., & Chu, X.L. (2022). Recent advances of chemometric calibration methods in modern spectroscopy: Algorithms, strategy, and related issues. *TrAC Trends in Analytical Chemistry*, *153*, 116648.

Wild, C. P., & Gong, Y. Y. (2010). Mycotoxins and human disease: A largely ignored global health issue. *Carcinogenesis*, *31*(1), 71–82.

Williams, P., Manley, M., & Antoniszyn, J. (2019). *Near-infrared technology: Getting the best out of light*. African Sun Media. https://books.google.com/books?hl=en&lr=&id=xSSyDwAAQBAJ&oi=fnd&pg=PP6&dq=Williams,+P.+(2014).+Near-Infrared+Technology:+Getting+the+Best+out+of+Light.+Food+Quality+%26+Safety,+8(3),+197-

204.+Williams+discusses+the+RPD+and+RER+values,+outlining+their+implications+for+model+performance+in+food+quality+assessments.&ots=DL_SwCjzBk&sig=hDywe3dnBv0KmoalqjLGjTgnyQ4

Williams, P., & Norris, K. (1987). *Near-infrared technology in the agricultural and food industries.* American Association of Cereal Chemists, Inc.

World Health Organization. (2003). Assuring food safety and quality: Guidelines for strengthening national food control systems. In *Assuring food safety and quality: Guidelines for strengthening national food control systems* (pp. 73–73).

Wrolstad, R. E., & Smith, D. E. (2017). Colour Analysis. In S. S. Nielsen (Ed.), *Food Analysis* (pp. 545–555). Springer International Publishing. https://doi.org/10.1007/978-3-319-45776-5_31

Wu, F., & Khlangwiset, P. (2010). Health economic impacts and cost-effectiveness of aflatoxin-reduction strategies in Africa: Case studies in biocontrol and post-harvest interventions. *Food Additives and Contaminants*, *27*(4), 496–509.

Yan, H., & Siesler, H. W. (2018). Hand-held near-infrared spectrometers: State-of-the-art instrumentation and practical applications. *NIR News*, *29*(7), 8–12.

Yanti, S. A., Soekardi, C., & Lubis, M. S. Y. (2018). Analysis of Parameter Roasting on Color and Peanuts Roasted Taste. *Aceh International Journal of Science and Technology*, *7*(2), 138–143.

Zhu, C., Fu, X., Zhang, J., Qin, K., & Wu, C. (2022). Review of portable near-infrared spectrometers: Current status and new techniques. *Journal of Near Infrared Spectroscopy*, *30*(2), 51–66.

APPENDICES

APPENDIX A

Analysis of Variance Moisture Content Verses Sample

Source	DF	Adj SS	Adj MS	F-Value	P-Value
SAMPLE	15	21.04	1.403	0.16	0.989
Error	2	17.40	8.700		
Total	17	38.44			

Analysis of Variance Protein Content Verses Sample

Source	DF	Adj SS	Adj MS	F-Value	P-Value
SAMPLE	15	17.2651	1.15101	156.23	0.006
Error	2	0.0147	0.00737		
Total	17	17.2799			

Analysis of Variance Fat/oil Content Verses Sample

Source	DF	Adj SS	Adj MS	F-Value	P-Value
SAMPLE	15	484.604	32.3070	2424.46	0.000
Error	2	0.027	0.0133		
Total	17	484.631			

Analysis of Variance Acid Value Verses Sample

Source	DF	Adj SS	Adj MS	F-Value	P-Value
SAMPLE	15	10.4679	0.697860	268.30	0.004
Error	2	0.0052	0.002601		
Total	17	10.4731			

Analysis of Variance Peroxide Value Verses Sample

Source	DF	Adj SS	Adj MS	F-Value	P-Value
SAMPLE	15	15.8393	1.05596	439.80	0.002
Error	2	0.0048	0.00240		
Total	17	15.8441			

Analysis of Variance-Free Fatty Acids

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Treatment	4	1.66473	0.416182	325.94	0.000
Error	5	0.00638	0.001277		
Total	9	1.67111			

Appendix B

Analysis of Variance Colour (L* versus Treatment)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Treatment	4	126.444	31.6111	50.96	0.000
Error	5	3.102	0.6203		
Total	9	129.546			

Analysis of Variance Colour (a* versus Treatment)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Treatment	4	3.018	0.7544	1.30	0.382
Error	5	2.895	0.5791		
Total	9	5.913			

Analysis of Variance Colour (b* versus Treatment)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Treatment	4	32.038	8.0096	25.11	0.002
Error	5	1.595	0.3190		

Analysis of Variance Colour (Chroma versus T)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Treatment	4	16.246	4.0614	8.81	0.017
Error	5	2.305	0.4610		
Total	9	18.551			

Analysis of Variance Colour (BI versus Sample)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Treatment	4	2837.0	709.25	17.08	0.004
Error	5	207.7	41.54		
Total	9	3044.7			

APPENDIX B

ETHICAL CLEARANCE

INSTITUTIONAL REVIEW BOARD SECRETARIAT

TEL:
E-MAIL:
OUR REF: IRB/C 3/Vol.2/0305
YOUR REF:
OMB NO: 0990-0271
IORG #: IORG0011497

13TH FEBRUARY, 2025

Mr. Joel Welbeck
Department of Agricultural Engineering
University of Cape Coast

Dear Mr. Welbeck,

ETHICAL CLEARANCE – ID (UCCIRB/CANS/2024/09)

The University of Cape Coast Institutional Review Board (UCCIRB) has granted Provisional Approval for the implementation of your study titled **Assessing the Safety and Quality of Peanut Butter on Ghanaian Market Using Portable Near-Infrared Spectroscopy.** This approval is valid from **13th February, 2025 to 12th February, 2026.** You may apply for a renewal of ethical approval if the study lasts for more than 12 months.

Please note that any modification to the project must first receive renewal clearance from the UCCIRB before its implementation. You are required to submit a periodic review of the protocol to the Board and a final full review to the UCCIRB on completion of the research. The UCCIRB may observe or cause to be observed procedures and records of the research during and after implementation.

You are also required to report all serious adverse events related to this study to the UCCIRB within seven days verbally and fourteen days in writing.

Always quote the protocol identification number in all future correspondence with us about this protocol.

Yours faithfully,

Kofi F. Amuquandoh
Ag. Administrator

Prof Fiifi Amoako Johnson
Chairperson

CHAIRPERSON
INSTITUTIONAL REVIEW BOARD
UNIVERSITY OF CAPE COAST