ESSENTIAL MINERAL ELEMENTS PROFILE OF SELECTED FOODS COMMONLY CONSUMED IN NIGERIA NECESSARY FOR MACHINE LEARNING OPERATION

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Abstract

Dietary mineral contents are essential nutritional elements with utmost importance which greatly contributes to both human and animal wellbeing to maintain sound health. It also assists plants to flourish adequately especially during growth. Deficiency in any of the essential micronutrients can result to life-threatening circumstances. In this study, essential elements (Ca, Fe, K, Na and Se) of two varieties of rice (NERICA 1 and FARO 59), two varieties of beans (pod borer resistant (PBR) and IT07K-318-33), plantain (*Musa paradisiaca spp*), Marabel irish potatoes (*Solanum tuberosum L.*), beef (*Bos taurus*) and chicken (*Gallus gallus domesticus*) commonly consumed in various forms were evaluatedto ensure seamless supervise machine learning operation for the calibration of a non-destructive equipment. Association of official analytical chemist (AOAC) standard experimental procedure was adopted and atomic absorption spectrophotometer (AAS) was used to obtain reference data of mineral contents for both raw and cooked samples of the selected food products. The experimental results revealed high values of 18.72mg/kg, 2.56mg/kg, 30.92mg/kg, 19.94mg/kg and 1.64mg/kg in Ca, Fe, K, Na and Se respectively across the food combinations. The result trend was observed with lowest spread of mineral values of 1.57mg/kg, 0.02mg/kg, 2.54mg/kg, 0.88mg/kg and 0.04mg/kg in the above trace elements sequence respectively. Generally, the results cascade within the daily acceptable limit for consumption as prescribed by food regulatory agencies and hence, fit and reliable for use as reference data for machine learning training for a non-destructive tool.

Keywords: mineral elements, micronutrients, machine learning, food products, non-destructive equipment.

Introduction

Cereal grains, legumes, root tubers and animal protein constitutes majority of food substance mostly consumed across the globe for nutritional benefits. These food items contributes significantly to human well-being when properly handled along the processing chain. Food processing along postharvest technique (cooking, soaking, baking, boiling, fermentation and drying) often affect food chemical compositions in an unpredictable ways from raw stage to finished product state. This is as a result of unresolved chemical and structural complexity of the food and the physicochemical modification mechanisms that occur during processing (Naravane and Tagkopoulos 2023). Micronutrients consist of minerals and vitamins and are both essentially required in small amount for the body metabolism. Most of the food mineral elements are categories into macronutrients (major), micronutrients (trace) and ultra-trace elements. The macro-mineral elements [e.g sodium (Na), calcium (Ca), potassium (K), magnesium (Mg), chloride (Cl), phosphorus (P) and sulfur (S)] are required in quantities greater than 100 mg / dl while the micro-mineral elements [copper (Cu), iron (Fe), potassium (K), zinc (Zn), selenium (Se), cobalt (Co), iodine (I), manganese (Mn), fluoride (F), chromium (Cr), boron (B) and molybdenum (Mo)] are desired in an amount less than 100 mg / dl while ultra-trace element (silicon, boron, arsenic and nickel) are found in animals and are believed to be essential for creatures (Gharibzahedi & Jafari 2017). The presence of series of these mineral elements can be obtained by consumption in composite form to acquire a good balance diet, this process help to enhance the hormone system and also can assist to regulate a standard heartbeat. Research revealed that some of the macro – and micro – elements are found in the structure of the teeth (Ca, F and P and) and body bones (Ca, Mg, Mn, P, B and F), whereas most micro-elements (Se, Cu, Mn, Mg, Zn and Fe) play vibrant role as a structural part in many enzymes (Gharibzahedi & Jafari 2017). Appropriate levels of these chemical elements have been demonstrated to be required to maintain optimal health as acute imbalances of these minerals can be potentially fatal to human (WHO/ FAO, 2004).

Although nutritional compositions of any food items depends on its plant uptake from the soil, postharvest handling and ingredients used during cooking, all these contributes to the palatability and the overall acceptability of the food product. Nutritional epidemiologists are currently concern about micronutrients such as Na, whose intake should be adequately monitored for individuals suffering from specific diseases like osteoporosis, kidney disease and stomach cancer. Whereas, fibre, whose excessive intake is detrimental and precarious for patients suffering from irritable bowel syndrome (IBS) is also of great concern (Ispirova et al., 2021). However, Ca is an essential mineral useful for building strong bones and a few quantities is required for human nerves, muscle work and heart function as the source of the elements include yoghurt, beans pudding, rice, meat, fish, cassava flake, milk, yam, fruit and fresh leafy green vegetable. Insufficient amount of Ca in the body can results to a disease called Osteoporosis. Fe constitute components of human red blood cells which helps to transport oxygen from the lungs through the organs to the muscles and to the cells. Fe can be obtained from the consumption of spinach, legumes (e.g. soybeans and beans), rice and leafy vegetables. Na can be derived from milk, rice and fresh vegetable and insufficient Na in human body can cause high blood pressure. Selenium is an antioxidant that increases immune function, it is commonly obtained from animal protein and a trace of this element can be obtained in legumes, cereal and tuber crops. Deficiencies in micronutrients can cause major public health risk to human-being especially the infant, lactating woman and pregnant women in many countries around the world because these class of people deserve extra care and requires adequate micronutrients to maintain normal growth and development particularly the infant (Soetan et al., 2010).

It has been established and supported by medical practitioners that nutritious food contributes immensely to human health which have become a core factor to today's society and are undeniable solution to the global health-crisis (Ispirova et al., 2021). Research attest to the current situation of human health challenges as globally associated to the epidemic of diabetes, obesity and inactivity, all connected to bad dietary habits. Many chronic diseases including cardiovascular disease (CVD), high blood pressure (BP), diabetes, some cancers and bone-health diseases are linked to poor dietary habits (Ijaz et al., 2020). Dietary assessment is essential for patients suffering from many diseases (especially diet and nutrition related ones), it is also very much desirable for professional athletes, individuals and industries to adopt current trend prior to food packaging and consumption, and because of the accessibility of meal tracking mobile applications and availability of non-destructive equipment to assess each meal to be consumed non-destructively. Industries, research institute and individual consumers are interestingly adopting the utilisation of these tool for health, fitness, or weight loss/gain due to technological advancement which have introduced machine learning (ML) techniques to ease the operation.

ML algorithms are mostly deployed in performing any specific task of interest which are uniquely different for numerous categories. Some predictive models based on ML algorithms are currently in use to simplify the micronutrient prediction based on few parameter. Other methods usually applied by food manufacturers for nutrition labels, by united state dietary agencies (USDA's) and dietary survey group to estimate nutrient intakes that investigators may use to evaluate correlations between intake and health outcomes is the retention factor (RF) (Nutrition retention factors, 2022).This have greatly assist to abridge the inherent complexity of conventional analytical means of evaluating the nutritional parameters in food substance. For instance, kinetic modelling based on an experimental data (label data) used for selected food establishes the relationship between nutrient concentration, temperature condition and time taken for such food preparation (Martinus, 2022; Bajaj and Singhal, 2020; Peleg et al., 2018).

Reference data generated from conventional laboratory means of food micronutrients analyses are increasingly becoming tedious and cumbersome to handle especially when large data are to be evaluated on the factory floor prior to food packaging (Kirk et al., 2022). However, all of these methods have limited potential. For instance, the kinetic models are difficult to scale up in order to capture more food and processing parameters, as these measurements are time-consuming, expensive and have many experimental challenges such as rapid degradation of certain chemical reagents (Naravane and Tagkopoulos 2023). Thus machine learning techniques been an alternative tool to handle data of such nature are gradually and efficiently adopted for ease of operation to eradicate drudgery during data processing. ML is capable of learning from multi-parametric transformation patterns between the compositions of raw and cooked foods data obtained from experimental data across diverse foods and cooking methods to make reliable predictions when trained on relevant datasets (Naravane and Tagkopoulos 2023). A number of food quality classifiers have adopted the used of hyperspectral data for the prediction of attributes related to nutrient profiles. Predicting nutrient (P_NUT) model have employed natural language processing (NLP) methods to predicts some nutritional (proteins, fats and carbohydrates) content of foods from a text description of the food (Ispirova et al., 2020) and a more recent version can predict macronutrients, from a recipe (Ispirova et al., 2021). USDA investigators predicted the content of three label nutrients (carbohydrates, protein and sodium) in processed foods from the ingredient list (Ma et al., 2021), using the Branded Foods datatype in food data central (FDC).

Food science, nutrition and Engineering refer to artificial intelligence (AI) as the application of conceptual algorithms, machine learning and deep learning techniques configured in a system to analyse, interpret and make informed and profound decisions from various datasets related to nutritional data, dietary patterns, and other health factors (Armand et al., 2024a; Chaves et al., 2023, Armand et al., 2024b). Researchers' engagement on the application of machine learning algorithms are yielding positively, in recent time, random forests have been deployed to analyse genetics and dietary data to understand how nutrients influence human genetic variations (Kosaraju et al., 2022). Likewise, collaborative filtering techniques are widely used in personalised nutrition recommendations, while deep learning methods such as convolutional neural networks (CNN) and transfer learning pre-trained models (Resnet, EfficientNet, etc.) have greatly assisted in identifying and classifying meals using food images to detect dietary patterns further to assess nutritional content (Kaur et al., 2023; Zitouni et al., 2022). Other ML multivariate algorithms useful for food and agricultural nutritional content predictions are not limited to recurrent neural network (RNN), K-nearest neighbor, decision tree, logistic regression (LR), naïve bayes, long short – term memory (LSTM), gray level co-occurance metrix (GLCM), support vector machine (SVM), least-square support vector, machine and artificial neural network. Researches' have shown that the most commonly used algorithms and complicated method does not necessarily always achieve the best prediction accuracy. Also, there was no single model capable of resolving all challenges encountered in ML and machine vision system (MVS). Thus, comparative strategy adopting multiple algorithms are widely used for model optimisation in the classification architecture where the best are chosen through the algorithm performance of the model visual output (Gholian-Jouybari et al., 2023). The objective of this study is to obtain elemental mineral element profile (datasets) of selected locally consumed food in Nigeria. These datasets serves as reference data for machine learning operation for training a model to predict future mineral elements of the selected food samples which can be deployed for the configuration of a non-destructive device for handling food and agricultural materials. Therefore, it is highly desirable to explore the trending technological tool for handling mineral elements of various food and agricultural products in line with the objective of this research work to further broaden the scope of food product evaluation using ML techniques.

2.0 Materials and Methods

2.1 Sample collection

Food samples used for this study are long grain rice, "Federal Agricultural Research Oryza" (FARO 59/NERICA 8), short grain rice "**New Rice for Africa"** (NERICA 1/FARO 55), white beans, "pod borer resistant" (PBR) variety were identified in Bauchi State Agricultural Development Programme (BSADP) centre while brown cowpea (IT07K-318-33) was obtained from International Institute of Tropical Agriculture (IITA) Kano Nigeria. Plantain (*Musa paradisiaca spp*), Marabel irish potatoes (*Solanum tuberosum L.*), beef (*Bos taurus*) and chicken (*Gallus gallus domesticus*) were all purchased in Muda Lawal market in Bauchi State of Nigeria. The samples were grouped into 2 separate parts were one section were evaluated at raw stage and the other part were cooked at moderate temperature using Maxi gas cooker. After, cooking the sample were taken to chemistry laboratory in Abubakar Tafawa Balewa University, Bauchi State, Nigeria for mineral element determination.

2.2 Sample Digestion

Prior to the digestion exercise, 1g of the each sample was weighed and placed in a beaker. Acid ratio 3:1:1 hydrochloric acid (HCL), nitric acid (HNO_3) and hydrogen peroxide (H_2O_2) was added respectively. The content was placed in a fume cupboard and heated at temperature range of about 50^0C – 80^0C for 50 minutes until solution reduced to its constant volume when the total volume finally reduced to break the complex bonds and release the sample into solution. The digested sample (solution) was allowed to cool and the solution was filtered into another beaker made up to 50 ml where distilled water was mixed thoroughly in 100ml sample bottles and are stored at room temperature in the laboratory prior to the final analyses. The samples were taken to atomic absorption spectrophotometer (AAS) machine for analysis to obtain the absorption and proportion of the mineral elements concentration in each of the samples as earlier conducted by (AOAC, 2010). Data obtained (reference data) in this study were subsequently fed into machine learning model (Figure 1) using python programming tool (3.12.5 version) and power business intelligence (PBI) software to gain an in-depth knowledge on the micronutrient composition of various food sample of interest. The machine learning algorithms adopted include random forest (RF), linear regression (LR) and decision tree (DT) multivariate to train each the model for optimum prediction of the mineral elements for the selected food samples.

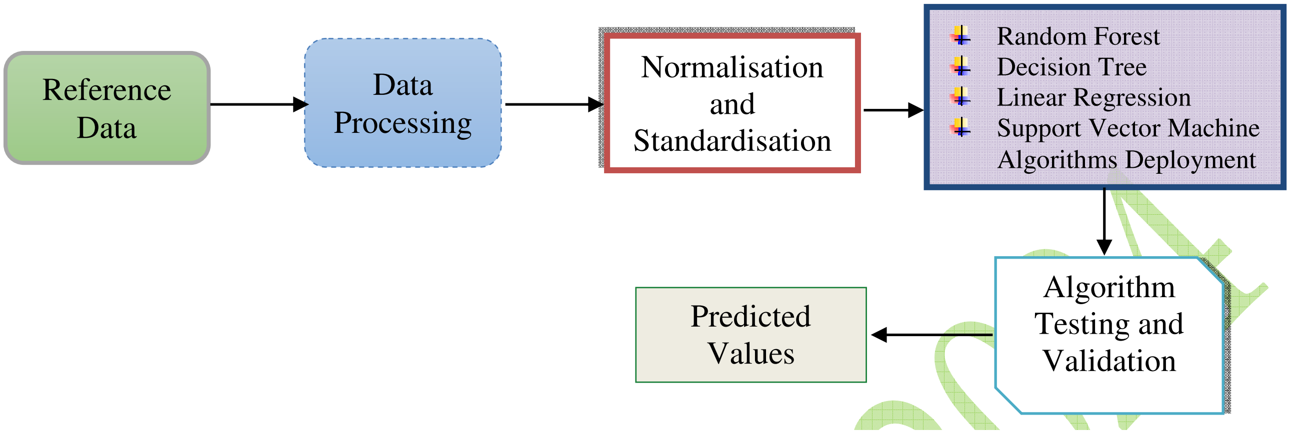

Figure 1: Model architecture for machine learning operation on essential mineral elements of selected food samples

During the supervised machine learning operation, random forest algorithm was considered for it optimum correlation in the prediction process. The regression analysis for the prediction in the model is expressed as given in equation (1).

$$\hat{x} = \frac{1}{N}\sum_{n=1}^{N} x_n \qquad 1$$

Where $\hat{x}$ is the final output of the ensemble model, **N** is represent the total number of trees in the random forest algorithm (and each tree contributes to the final prediction) and x_n is the prediction made by the n-th tree for the input (reference data). Each tree in the random forest's algorithm independently makes its own prediction based on the features of the input.

3.0 Results and Discussion

3.1 Results

Generally, the essential mineral contents of the selected food samples used for this study were determined and reported in mg/kg fresh weight of edible food as presented in Tables 1a, 1b and 1c. Essential mineral elements are required in substantial amount in human body for various physiological and metabolic activities to maintain healthy body structure. Calcium (Ca) is one of the most mineral requirement of the body and its function include regulating muscular contractions including heartbeat, blood clotting and formation of strong bones and teeth (WHO 2004). Majority of the values of cooked samples used for this study shows significant increase in Ca elements as compared to the raw sample for similar composition as indicated in Figure 2. While IT07K-318-33 cowpea shows different pattern where the raw sample contains higher Ca composition (14.45mg/kg) as compared to the cooked sample with Ca value of 5.19mg/kg. Similarly, PBR and cassava flake follow the same trend as IT07K318-33 cowpea results (Figure 2). The measured values of calcium in this study are comparatively closer to the levels found in imported rice samples (79.30±9.2mg/kg) obtained from other researchers, but significantly lower than other varieties of NERICA (4, 12, and 14) and Ethiopian rice reported by Tegegne et al., 2020. The difference in Ca levels in samples obtained from different locations could be due to different levels of Ca uptake from the soil. Moderate consumption of Ca is vital for human health and immune system, blood clotting and blood pressure regulation. Values obtained in this study were all well below the daily limit of 3500 mg/day as recommended by World health organization daily for Ca intake (WHO, 2009). Thus, an individual whose major diet is rice (NERICA 1 and FARO 59 only) could be prone to diseases such as osteoporosis and hypocalcemia that have been linked to calcium deficiency.

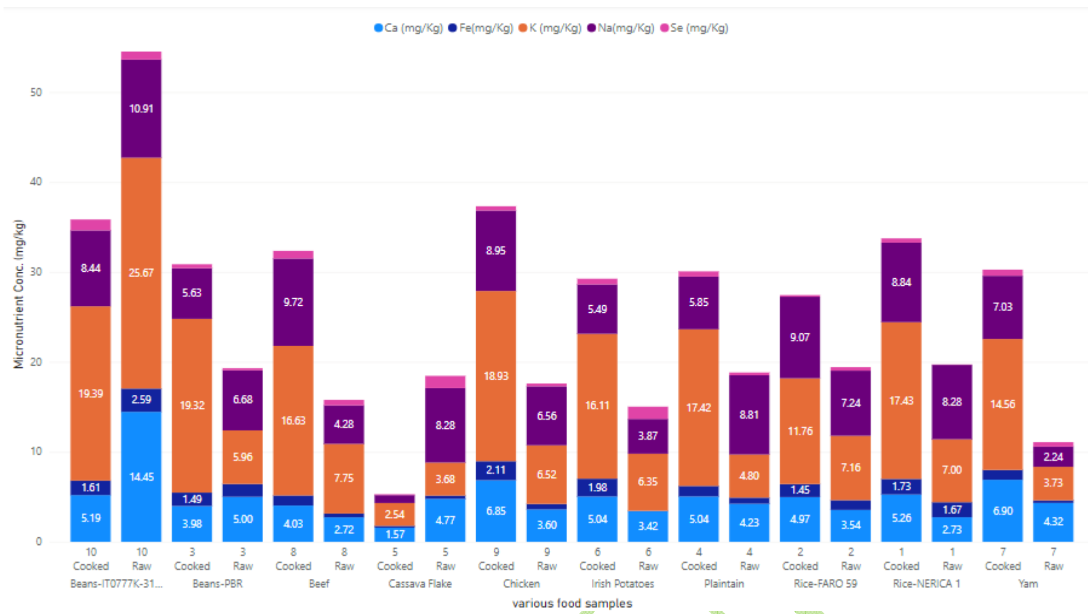

Figure 2: Macro-and-micro-nutrients of various food sample at raw stage and after cooking

Table 1a: Essential Mineral Elements of Various Food Samples

Mineral Elements	Raw food samples evaluated									
	N1-Rice	F59 Rice	PBR	PL	CF	IP	Yam	Beef	Chicken	BB
K (mg/Kg)	7.00	7.16	5.96	4.8	3.68	6.35	3.73	7.75	6.52	25.67
Na(mg/Kg)	8.28	7.24	6.68	8.81	8.28	3.87	2.24	4.28	6.56	10.91
Fe(mg/Kg)	1.67	1.09	1.43	0.68	0.36	0.023	0.29	0.42	0.61	2.59
Ca (mg/Kg)	2.73	3.54	5	4.23	4.77	3.42	4.32	2.72	3.6	14.45
Se (mg/Kg)	0.04	0.39	0.24	0.3	1.36	1.36	0.5	0.61	0.31	0.89
Mineral Elements	**White Cooked NERICA 1 with various composite**									
	N1-Rice only	N1-Rice + PBR + PL + Beef	N1-Rice + BB+ IP + Chicken	N1-Rice + Yam + S + Beef	N1-Rice + BB + PL + IP + Chicken	N1-Rice + PBR + PL+ Beef	N1-Rice + Chicken	N1-Rice + Beef	N1-Rice + BB+ PL + Beef +Yam	N1-Rice + PBR + IP + Chicken
K (mg/Kg)	17.43	10.44	26.01	24.91	30.91	17.09	29.88	21.34	19.01	19.79
Na(mg/Kg)	8.84	19.94	12.01	9.98	12.09	18.89	12.98	9.96	12.21	20.91
Fe(mg/Kg)	1.73	3.07	1.65	1.79	2.11	1.59	1.84	2.56	1.82	2.24
Ca (mg/Kg)	5.26	18.72	11.54	14.55	9.54	9.83	12.86	11.76	10.09	10.86
Se (mg/Kg)	0.48	0.86	1.34	0.79	0.83	1.48	1.11	0.95	0.99	1.14
Mineral Elements	**White Cooked FARO-59 Rice with various constituent**									
	F59 Only	F59 + PBR + PL+ Beef	F59 + BB + IP + Chicken	F59 + Yam + Salad + Beef	F59 + BB + PL + IP + Chicken	F59 + PBR + PL + Beef	F59 + Chicken	F59 + Beef	F59 + BB + PL + Beef +Yam	F59 + PBR + IP + Chicken
K (mg/Kg)	11.76	10.98	24.09	23.98	29.43	15.12	27.93	19.4	29.2	20.09
Na(mg/Kg)	9.07	16.98	12.87	10.33	11.76	18.43	14.3	10.98	13.03	18.99
Fe(mg/Kg)	1.45	2.98	1.49	1.87	2.08	1.59	2.27	1.87	1.94	2.39
Ca (mg/Kg)	4.97	9.08	10.76	13.42	9.01	10.33	9.91	10.92	8.98	11.56

Se (mg/Kg)	0.18	0.68	1.6	0.87	0.93	1.48	0.95	0.83	1.09	1.08

N1-Rice = NERICA 1 Rice, F59 = FARO 59 Rice, PBR = white beans, "pod borer resistant", PL = Plantain, CF = Cassava flake, IR = Irish potatoes, BB = brown cowpea (IT07K-318-33), S = salad

Table 1b: Essential Mineral Elements of Various Food Samples

Mineral Elements	Jollof Cooked NERICA 1 with various additional constituent									
	N1-Rice only	N1-Rice + Chicken	N1-Rice + Beef	N1-Rice + PBR+ Salad	N1-Rice + Fried + S + Beef	N1-Rice + PL + Chicken	N1-Rice + BB + Irish	N1-Rice + IP+ PL+ Chicken	N1-Rice + Yam + Beef	N1-Rice + Yam + PL + IP+ Chicken
K (mg/Kg)	17.43	12.87	29.06	23.22	30.92	17.76	26.49	18.62	24.01	18.71
Na(mg/Kg)	8.84	16.83	13.55	10.87	12.98	12.07	9.94	11.03	12.98	17.63
Fe(mg/Kg)	1.73	2.11	1.45	1.59	1.93	1.79	1.53	2.31	1.87	2.17
Ca (mg/Kg)	5.26	12.01	11.37	9.95	10.23	9.11	9.54	8.73	11.56	12.47
Se (mg/Kg)	0.55	0.77	0.97	0.91	0.79	1.63	0.89	0.86	0.98	1.13

Mineral Elements	Jollof Cooked FARO 59 with various additional constituent									
	F59 Only	F59 + Chicken	F59 + Beef	F59 + PBR + Salad	F59 + Fried + Salad + Beef	F59 + PL + Chicken	F59 + BB + IP+ Beef	F59 + IP + PL + Chicken	F59 + Yam + Beef	F59 + Yam + Plantain + IP + Chicken
K (mg/Kg)	11.76	11.76	30.06	24.52	28.99	19.92	28.91	19.72	25.32	20.71
Na(mg/Kg)	9.07	17.89	16.42	8.93	9.88	10.08	11.47	9.73	10.56	15.91
Fe(mg/Kg)	1.45	1.74	1.86	2.77	1.88	2.11	1.37	2.13	1.99	2.56

Ca (mg/Kg)	4.97	8.09	9.36	10.83	8.01	9.66	9.03	7.14	10.98	14.96
Se (mg/Kg)	0.18	0.21	0.59	0.63	0.97	0.91	0.98	1.43	1.37	0.94

N1-Rice = NERICA 1 Rice, F59 = FARO 59 Rice, PBR = white beans, "pod borer resistant", PL = Plantain, CF = Cassava flake, IR = Irish potatoes, BB = brown cowpea (IT07K-318-33), S = salad.

Table 1c: Essential Mineral Elements of Various Food Samples

Mineral Elements	Cooked Food Samples							
	PBR only	**Plantain only**	**Cassava Flake only**	**BB only**	**Irish Potatoes only**	**Yam only**	**Beef only**	**Chicken only**
K (mg/Kg)	19.32	17.42	2.54	19.39	16.11	14.56	16.63	18.93
Na(mg/Kg)	5.63	5.85	0.88	8.44	5.49	7.03	9.72	8.95
Fe(mg/Kg)	1.49	1.17	0.2	1.61	1.98	1.09	1.12	2.11
Ca (mg/Kg)	3.98	5.04	1.57	5.19	5.04	6.9	4.03	6.85
Se (mg/Kg)	0.44	0.59	0.1	1.21	0.63	0.68	0.85	0.47

Mineral Elements	**Yam and Cassava Flake with additional constituents**			
	Yam + Beef + Stew	**Yam + Stew**	**Cassava Flake and Beef + Stew**	**Cassava Flake + Stew**
K (mg/Kg)	17.68	24.08	26.78	14.59
Na(mg/Kg)	15.03	9.58	7.95	9.78
Fe(mg/Kg)	1.47	1.45	1.67	1.03
Ca (mg/Kg)	13.98	20.98	12.95	12.07
Se (mg/Kg)	0.64	0.89	0.83	0.83

PBR = white beans, "pod borer resistant", BB = brown cowpea (IT07K-318-33).

The result also revealed that Ca constituents varied significantly from 1.57 mg/kg to 20.98 mg/kg across all the food samples used for this study. However, the maximum (20.98 mg/kg) and minimum (1.57mg/kg) values were obtained from yam + stew and cassava flake respectively (Table 1c). The high value of Ca observed in the food sample can be as a result of high calcium uptake from the soil for the yam sample and combination of other condiments contained in the stew. Na element was high (20.91mg/kg) in white rice based composite (NERICA 1 + PBR + Irish + chicken) and low (0.88mg/kg) in cassava flakes. Interestingly, Fe and Se contents across all the non-composite food samples are relatively insignificant. However, K compositions in majority of the non-composite food samples shows that higher values in the cooked meal except for IT07K318-33 (brown beans) and cassava flakes which shows different pattern with an higher values in their respective raw sample over the cooked meal (Figure 2).

Sodium (Na) is necessary for appropriate maintenance of body electrolyte and fluid balance, heart function and specified metabolic activities, muscle contraction and nerve transition. Na content of most dishes analysed in this work can be considered relatively low compared with the daily recommended intake (DRI). This study revealed that highest values of Na across the studied samples was observed to be 20.91mg/kg in cooked white rice based composite –meal (NERICA 1 + PBR + Irish + chicken) while the lowest values of 8.84 mg/kg was reported in both white and jollof NERICA 1 cooked independently (Figure 3). Excessive use of dietary salt and sodium containing compounds such as monosodium glutamate (MSG) used in cooking, consumption of these dishes cannot be an issue of health concern or a risk factor for cardiovascular disease (CVD). But, excessive sodium intake has been associated with high blood pressure and stiffening of arterial walls and therefore a risk factor for CVD (Morakinyo et al., 2016; WHO, 2006). The daily recommended range of sodium in the human diet is 240 mg/day. Hence, consumption of studied samples in this work are consider safe for humanity.

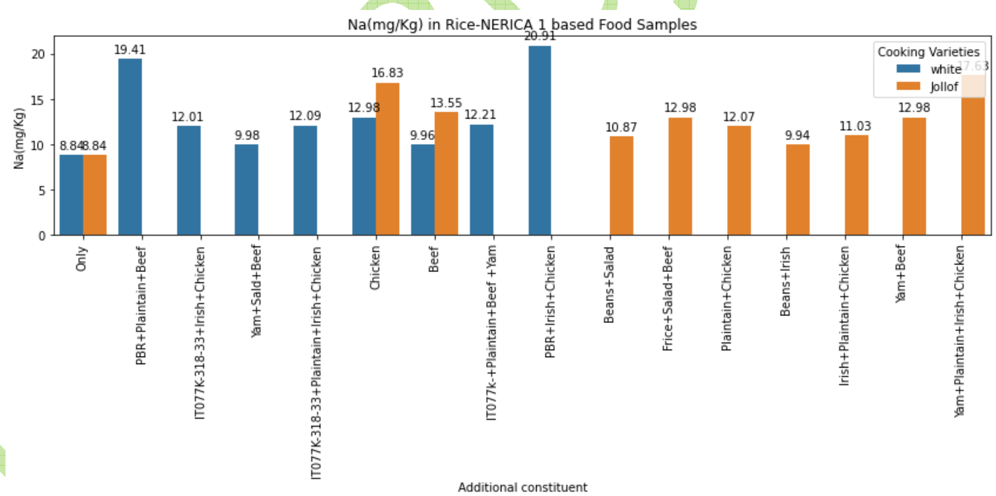

Figure 3: Na concentration of NERICA 1 based cooked food sample

Iron (Fe) as one of the body required microelements helps in detoxification processes. It is desired for the formation of hemoglobin and myoglobin in red blood cells, which carries oxygen from the lungs to the body cells needed for energy metabolism. It is also required for many proteins and enzymes functionality to prevent anaemia. Anaemia has been shown to be linked maternal mortality and premature child birth (Morakinyo et al., 2016). Highest values of Fe contents (3.07mg/kg) in the variety of food samples used was discovered in cooked white rice – based food composition (NERICA 1 + PBR + plantain + beef) while the lowest result (0.20mg/kg) was obtained in cooked cassava flakes (*eba*). However, high amounts of Fe can be hazardous because human-beings do not have a physiologic pathway for its elimination except that it undergo normal gastrointestinal digestion (Gharibzahedi and

Jafari 2017). Meanwhile, Fe is the most common micronutrient deficiency in the world. Women of childbearing age are the highest risk group because of menstrual blood losses, pregnancy, and lactation. Thus, dietary iron is best supplied by consumption of foods like Rice, Yam, beans, beef, as well as plantain as observed in the outcome of this study. This is an indication that consumption of cooked cassava flakes and other food composite contained in this study are considered safe as the micronutrients therein are in adequate moderation.

Potassium (K) is essential for proper fluid balance, nerve transmission, muscle contraction, suitable maintenance of blood pressure and waste elimination (Gharibzahedi and Jafari 2017). Low potassium is associated with a risk of high blood pressure, heart disease, stroke, arthritis, cancer, digestive disorders, and infertility. Maximum and minimum potassium values of 30.92 mg/kg and 10.44 mg/kg were discovered in combined jollof rice base - meal (jollof NERICA 1 + fried NERICA 1 + beef) and white rice based meal (NERICA 1 + PBR + plantain + beef) respectively. Highest value of K recorded in this study was lower than the values previously prescribed as the daily recommended dietary allowance and adequate intakes (5.1g/day highest and 3g/day lowest) for men, pregnant and lactating women within the age bracket of 19 – 50years (Morakinyo et al., 2016). Although, there are abundant evidence that a reduction in dietary sodium and increase in potassium intake decreases BP, incidence of hypertension, and morbidity and mortality from CVD (Whelton and He 2014). Therefore, people with low potassium can explore the meal composition in this study or improve their respective diets with potassium supplements to prevent or treat some of the health challenges associated with potassium deficiency.

Selenium (Se) is enriched by making special proteins, called antioxidant enzymes that play an important role in protecting the body from the damaging effects of heavy metals, free radicals and other harmful substances. Se is also known for stimulation of immune system and forms part of the enzyme that activates the thyroid hormone thereby protecting the organism from various virus (Gharibzahedi and Jafari 2017). The values of selenium in this study ranged between 0.1mg/kg (0.1 $\mu g/g$) in cooked cassava flake dish to 1.63mg/kg (1.63 $\mu g/g$) in jollof rice composite – meal (jollof NERICA 1 + plantain + chicken) samples. The maximum value of Se obtained in this study was discovered to be within the acceptable and recommended level (60μg) by national agency for food and drug administration and control (NAFDAC, 2021) and national institutes of health (NIH, 2024) daily recommended dietary allowances (RDAs) for selenium (55μg/ ounce for male, 55μg/ ounce for female, 60μg/ ounce for pregnant and 70 μg / ounce, for lactating women). Moderate consumption of various dishes (both singlet and composite) as conducted in this study is an indication that all the food samples in concern are safe and are recommended for intake for maximum health benefits.

3.2 Prediction from supervised machine learning model

The overall predicted values obtained from random forest machine learning algorithm used for the datasets of the mineral elements across all the food samples are presented in Table 2.

Table 2: Evaluated and Predicted Mineral Elements Constituents in the Food Samples

Mineral Elements	Raw sample concentration		Cooked sample concentration	
	Measured value (mg/kg)	Predicted value (mg/kg)	Measured value (mg/kg)	Predicted value (mg/kg)
K	7.86	23.45 ± 1.94	20.72	23.47 ± 0.28
Na	6.72	10.29 ± 0.10	11.83	16.18 ± 0.44
Fe	0.92	2.38 ± 0.84	1.83	2.08 ± 0.03
Ca	4.88	12.06 ± 0.10	9.72	9.85 ± 0.02
Se	0.60	0.81 ± 0.16	0.88	1.03 ± 0.01

Predicted values obtained are mean ± RMSE (Root mean square error)

4.0 Conclusion

Essential mineral elements of great importance to human health are evaluated in this study with the additional aim to enable researchers' obtain locally consumed food datasets for machine learning operation. Standard recommended techniques was employed to obtain these label data in the laboratory. The data from various food samples were fed to random forest (RF), linear regression (LR) and decision tree (DT) algorithm using python programming language for predictions while power BI package was used to analyse these data gaining insight into the trend of hydrothermal treatment on the examined food samples. Under normal circumstances, the average daily dietary intake for each micronutrient that is required to sustain normal physiologic functions is measured in milligrams or smaller quantities. The overall outcome of the study revealed that the dataset obtained in this study were adequately within the recommended dietary allowable daily intake as prescribed by various food regulatory agencies and hence make the examined foods safe for consumption and fit for supervise machine learning training.

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