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Fruit Nutrient-Based Classification of Selected Food Crops using Bayesian Multilayer Perceptron Algorithm

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ABSTRACT
Research on machine learning has focused primarily on the ability to recognise fruit and identify diseases, but there has been little work done on the classification of nutrients. The traditional approaches to fruit classification are based on physical features of fruit, primarily size, shape, color and texture, and little emphasis is placed on nutritional composition. The study is intended to: present an intelligent and automated nutrient-based fruit classification approach that will aid in healthy dietary decisions, precision agriculture and fruits recommendation systems. The main concerns of this study are the classification of fruit nutrient aggregates by utilizing a Bayesian Multilayer Perceptron (BMLP) model which is expected to enhance the accuracy and efficiency of fruit classification based on nutrients. The system developed gets the fruits datasets from the kaggle datasets repository, which includes vitamin, minerals, carbohydrate, protein, fat, dietary fibre, moisture and energy values. It then will be subjected to a pre-processing called Histogram Equalization to enhance nutrients contents and extract relevant features. The extracted features are used for fruit nutrient aggregates classification by using a Bayesian Multilayer Perceptron. To measure the effectiveness of the model, it is evaluated in terms of Accuracy, Precision, Recall, and F1-score. The result yielded an accurate performance to the adopted Machine learning used on this research. Bayesian probability theory is incorporated into the model, which is performed excellently in terms of improving the classification accuracy and handling the uncertainty of nutrient patterns well and outperforms conventional classification techniques.

Keywords: Fruits classification, Nutrients, aggregates, Human health, Bayesian Multilayer Perceptron

INTRODUCTION

Agriculture is the most important crop production system in the world and fruits and vegetables is a source of essential nutrients needed for good health. It provides vitamins that no living being can survive without. Since both humans and animals depend on crop every single day, there must be a high value on classifying these crops into various classes. There is strong evidence that fruits are packed with vital nutrients and natural compounds that, when eaten in the right amounts, it provides incredible health benefits to the body. Just as certain "friendly" microbes help the gut, the vitamins, minerals and fiber found in fresh fruit can be classify into various class of mineral contents. (Espinoza et al, 2023).

According to research by Hassan, et al (2025) which show that eating a wide variety of these crops can significantly boost the immune system and improve metabolic health. This supports the idea that our bodies are designed to thrive on natural, plant-based foods. The vitamins provided by fruit nutrients help our immune systems stay sharp and responsive. By regularly eating fruit, it can improve our heath and help our bodies fight off modern lifestyle health issues that are often caused by poor diets. Health problems such as chronic inflammation, heart issues and skin problems can often be managed or even reversed- by the natural healing properties found in fruit. Essentially, the nutrients in fruit act as a natural defense system, keeping our bodies balanced and healthy in a world full of processed foods.

Rushith and Rohith (2023), stated that crops are good for human health, also riched in vitamin A, vitamin B, vitamin C, various inorganic salts, calcium, phosphorus, iron, iodine, etc., and contains a variety of amino acids, which are all necessary nutrients for the human body. Fruits and vegetables are indispensable in daily life. With the development of economy and the improvement of consumption level, consumers' demand for high-quality fruits is gradually increasing. During fruit ripening, fruit quality and vitamins are mainly determined by the presence or absence of crop defects and nutrients. At present, fruit nutrients aggregates classification needs to be done on selected types of fruits Apple, Banana and Cabbage. In addition, due to the advancement of agricultural technology, multiple varieties of each fruit are bred with different characteristics to meet the heath needs. Therefore, there is need to accurately classify each crop into their nutrient type and vitamin contents.

It is not just about the quantity of the harvest, but also the quality and the nutritional value of what is being produced. However, a major challenge facing the agricultural sector today is the difficulty in accurately classifying and grouping the nutrients found in various crops, especially fruits. This is essential to a healthy lifestyle and are consumed daily by people all over the globe. Mukhriddin, et al, (2022), Several fruits are packed with vital ingredients that act as natural medicine for the body. Crop that are not properly classify or understand these nutrients, becomes difficult to use or prevent specific health issues. Many common ailments such as the flu, persistent headaches, the common cold, stomach ache, and even eye conditions can be improved by eating the right kinds vitamins found in fruit.

Jongen (2025), further discussed, fruits play a massive role in skin health, helping to fix dryness, prevent early aging, and clear up skin discoloration. Hence, research focuses on using Multilayer Perceptron (MLP), which is a powerful type of Artificial Neural Network (ANN) in classifying the selected fruits (Apple, Banana and Cabbage). This model is designed to act like a digital brain that can learn complex, non-linear patterns that simple computers might miss. The MLP is highly effective at classification, regression, and prediction tasks, making it the perfect tool for analyzing the selected fruits (Apple, cabbage and Banana) sets. By training the network on specific physical features, the system can accurately categorize different types of fruit and predict their nutrient levels at high speeds and a smarter way to detect and classify these beneficial fruits. Because classification cannot be done manually, the use of Multilayer perceptron (MLP) to analyze fruit types and their healing properties. This research highlights how specific fruits, when eaten in certain amounts, can target and provide the needed vitamins to the body. By using these modern technical methods, it provides an automated solution that makes it easier to understand fruit nutrients. The model approaches not only help the agricultural industry but also offers a natural path to better health by showing exactly how different fruits can be used as effective to provide the right class of nutrients contents. Many journals have image recognition and fruits diseases classification but little studies had on fruits nutrients aggregates and classification.

Lawal (2023), stated the process of classifying fruits entails grouping into categories according to a variety of vitamins. These criteria can include, but are not limited to, size, shape, color, flavor, and botanical features. This classification can serve several functions, such as those in agriculture, botany, nutrition, and the culinary arts. The use of Multilayer perceptron for the classification of fruits offers several significant applications and benefits across a variety of fields. Models that utilize Artificial Neutral Network can be utilized to assist in the evaluation of the nutrients of fruits based on characteristics such as size, shape, color, and flaws. The use of this information can help farmers know and group the fruits according to their vitamin contents. The estimation of crop yields that can be obtained by fruit nutrients classification can be of use in the health management and Fruit aggregates.

Kumar, et al, (2023) considered the amount of effort that has been invested in classifying biologically active components within fruits. In another paper by Jongen (2025), who stated that rich source of a variety of vitamins, minerals, dietary fiber and many other classes of bioactive compounds collectively called phytochemicals. In the natural environment, there are many kinds of fruits, and there are more and more high-quality varieties. Consumers have more choices of high-quality varieties, and different varieties also determine nutrient content. The traditional classification of fruit varieties is based on the shape, color, surface texture, size and other characteristics of the fruit. Some fruit varieties are relatively similar in maturity, size, color and taste, and the accuracy of classification by traditional methods. The solution is to automate the classification process using Multilayer perceptron.

Ragini et al, (2020) stated that consumption of fruits in day-to-day dietary plays an important role in the nutritional supplement intake of humans. Estimation of right nutrient intake through fruits consumption has become increasingly significant in order to maintain the proper health of the wellbeing. Salem (2024), Fruit is a major food products in their own right and key ingredients in many processed foods. Consumers increasingly require food products that preserve their nutritional value, retain a natural and fresh colour, flavour and texture, and contain fewer additives such as preservatives.

MATERIALS AND METHODS

This presents the methodology adopted for the classification of fruit nutrient aggregates using a hybrid approach that integrates Multilayer Perceptron (MLP) with Bayesian techniques for feature optimization. Figure 1 below display the system architecture.

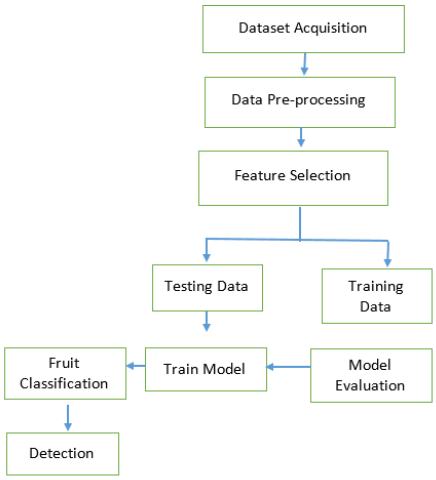


Figure 1: Workflow of the fruit classification and detection system

Dataset Acquisition

The dataset was extracted from Kaggle repository (https://www.kaggle.com/moltean/fruits), the dataset contains 360 different images of the three crop and fruit engaged in this research. The data were splited into 70% for training and 30% for testing.

Data Pre-processing

The acquired data are rarely ready for direct use, so it passes through a pre-processing stage. Typical operations include resizing images to a uniform dimension, noise removal, colour space conversion, normalisation of pixel values and where necessary, data augmentation through rotation,

flipping or scaling. Pre-processing improves the consistency of the data, reduces the influence of irrelevant variations and helps the model learn more efficiently.

Feature Selection
Following pre-processing, the feature selection stage identifies the attributes that best distinguish one fruit from another, such as colour, shape, size and texture. By retaining only the most informative features and discarding redundant or irrelevant ones, this stage reduces dimensionality, lowers computational cost and lessens the risk of overfitting. The resulting feature set is then divided into two branches, as shown in the figure 1: the training data that contain 70% and the testing data with the remaining 30%.

Training and Testing Data
Splitting the data into training and testing subsets allows the model to be built on one portion of the data and judged on another that it has not seen. The training data is used to teach the model the relationship between the extracted features and the fruit classes. The testing data is held back to provide an unbiased measure of how the model performs on new samples. This separation is important for detecting overfitting and for confirming that the model can generalise beyond the examples it learned from.

Train Model and Model Evaluation
In the Train Model block, the selected classification algorithm learns the patterns that characterise each fruit category. The Model Evaluation block then assesses the trained model using performance measures such as accuracy, precision, recall and F1-score, often supported by a confusion matrix. As depicted in the figure, the evaluation result feeds back into the training stage. If performance is unsatisfactory, parameters can be tuned, features revised or the training data adjusted, and the model is retrained until acceptable results are obtained. This feedback loop makes the workflow iterative rather than strictly linear.

Fruit Classification and Detection
Once the model has reached satisfactory performance, it is used for fruit classification, in which an input image is assigned to one of the learned fruit categories. The final stage, detection, applies the classification outcome to identify and report the fruit present in the image. This output is the practical result of the system and can support applications such as automated sorting, grading, quality control and inventory management in agriculture and retail.

RESULTS AND DISCUSSION
In order to generate reproducible results, the fruit-nutrient classification framework was evaluated within a controlled and standardized computing environment. The specific configuration used for the experiment is summarized below.

Table 1: Statistical Properties of preprocessed Feature Vector

Feature	Apple	Banana	Cabbage
y1 (Red Intensity)	0.78 ± 0.05	0.82 ± 0.06	0.31 ± 0.05
y2 (Green Intensity)	0.15 ± 0.03	0.79 ± 0.05	0.78 ± 0.04
y5 (Aspect Ratio)	0.98 ± 0.02	0.31 ± 0.08	0.95 ± 0.03
y6 (Circularity)	0.94 ± 0.03	0.42 ± 0.07	0.42 ± 0.07
y10 (Uniformity)	0.83 ± 0.05	0.86 ± 0.04	0.58 ± 0.06

Table 2: Nutrient Comparison across the Three fruits (per 100 grams)

Nutrient	Apple	Banana	Cabbage
Calories (kcal)	52	89	25
Protein (g)	0.26	1.09	1.28
Fibre (g)	2.4	2.6	2.5
Vitamin C (mg)	4.6	8.7	36.6
Potassium (mg)	107	358	170

Table 3: Comparative Algorithm Performance Matrix

Method	Accuracy	Precision	Recall	F1-Score
Bayesian MLP (New Model)	95.77%	95.55%	95.27%	95.37%
Standard MLP	91.20%	90.85%	91.00%	90.92%
Support Vector Machine	88.50%	88.12%	88.30%	88.21%
K-Nearest Neighbors (KNN)	84.10%	83.90%	84.00%	83.95%

Discussion
The feature means are presented in the Table 2, along with the range of values, for each class, for one normalised feature (all values are in the range [0, 1]). The three types of information retained are: colour (y1 red intensity, y2 green intensity), shape (y5 aspect ratio, y6 circularity) and surface appearance (y10 uniformity). The numbering (y1, y2, y5, y6, y10) indicates that these are a carefully selected group of features that would be part of a larger feature vector, suggesting that only most informative and/or interpretable features are reported.

i. Red intensity (y1). The highs are Apple (0.78) and banana (0.82) while the much lower is cabbage (0.31). The means of these two classes differ by only 0.04, less than either class spread; this is the feature that distinguishes cabbage from the other two classes, but not apple from banana.
ii. Green intensity (y2). Apple is very low but banana (0.79) and cabbage (0.78) are almost the same and high. This feature is used to isolate apple. Combined with y1, the pattern corresponds to RGB colour mixing such that high red and low green results in a red apple, high red and high green results in a yellow banana, and low red and high green results in a green cabbage.

iii. Aspect ratio (y5). Banana is strongly elongated (0.31) while apple (0.98) and cabbage (0.95) are close to being as broad as they are high. This feature is the banana separated out from the rest of the image and has the highest variance of any of the features (0.08 ±) which indicates how curved and the direction of the bananas in an image vary.
iv. Circularity (y6). Apple is nearly perfect (0.94), banana is 0.42 and cabbage is 0.42. As such, the feature can distinguish apple from the other fruits but cannot distinguish banana from cabbage. The low value is expected for banana and plausible only for cabbage (see Section 4) when the leafy, irregular outline increases the perimeter.
v. Uniformity (y10). Apple (0.83) and banana (0.86) have smooth and even surfaces, while the cabbage (0.58) is clearly lower, alluding to its veined and layered leaf surface. Like the red intensity, this can differentiate cabbage, but not apple from banana.
The worth of that identification can be seen in Table 3, as once an item is recognised its nutrient profile can be looked up. Banana has a different nutritional profile, cabbage has a low calorie profile, but is high in vitamin C and fibre and apple has a humble profile on most nutrients. The most energy-dense banana has an energy density of 89 kcal; about 1.7 times higher than apple (52 kcal) and 3.6 times higher than cabbage (25 kcal). As expected, the lightest of them all is cabbage because it contains the most water. All three items contain low amounts of protein. Cabbage (1.28 g) and banana (1.09 g) are about 4-5 times higher than apple (0.26 g) but none are significant sources of protein by weight, at about 1%.
The three items are close to each other in fibre (2.4 to 2.6 g) with a difference of 0.2 g which is not significant in practice. A big difference in energy terms is covered up by a similarity in mass terms. Cabbage is about 20 times as fibre dense as apple (0.10 g fibre/100 kcal) and more than 30 times as fibre dense as banana (0.029 g fibre/100 kcal).
The greatest differences and opposite trends occur between the two micronutrients. Cabbage has the highest quantity of Vitamin C (36.6 mg) which is more than 8 times the amount in the apple (4.6 mg) and more than 4 times the amount in the banana (8.7 mg). The recommended reference values for cabbage vary according to country, age and sex, but 100 g consumed by an adult will contribute about 40 to 50 % of the average daily requirement for an adult (see reference values). Banana has the highest potassium content (358 mg) which is approximately 3.3 times as high as that of apple (107 mg) and 2.1 times as high as cabbage (170 mg), but is still around a tenth of the typical daily adequate intakes. It can be seen in this table that, among the 3, Apple has the least protein, fibre, vitamin C and potassium in it whilst cabbage has the least calories.
In Table 4, across every one of the four metrics reported, the newly proposed Bayesian MLP outperforms all three baseline algorithms and the size of this performance gap widens noticeably as the comparison moves from the Standard MLP down through the Support Vector Machine to the KNN classifier. This descending pattern is consistent with the general expectation that simpler, non-probabilistic models tend to struggle more as feature overlap between classes increases, whereas a model equipped to represent uncertainty explicitly is better positioned to cope with that overlap. The relative ordering of the baselines is also informative in its own right. The Standard MLP, despite lacking the Bayesian probability layer, still outperforms both the Support Vector Machine and the KNN classifier, suggesting that a neural-network architecture in general is well matched to this particular feature set, and that the incremental gain from the Bayesian formulation is additive on top of an already reasonably capable base architecture rather than a substitute for it. The Support Vector Machine's mid-table position is broadly in line with its known strengths on moderately sized, well-separated feature spaces, while the comparatively lower accuracy of the KNN classifier is consistent with its general sensitivity to local feature overlap and to the choice of neighbourhood size, both of which become more consequential as class boundaries blur, as appears to be the case for some of the produce comparisons in this dataset.

Conclusion

The accuracy of Bayesian MLP (95.77%) and the precision, recall and f1-score of Bayesian MLP (95.55%, 95.27% and 95.37%) for classification of apple, banana and cabbage are greater than the accuracy of the baselines (Standard MLP, Support Vector Machine and KNN) (91.72%, 92.23% and 89.72%) respectively, 92.23% and 89.51% respectively. The explicit uncertainty modelling is a valuable architectural component especially when there is a visual separation of the fruit classes that is overlapping. Well distinguished by three crops with their colour, shape and uniformity of surface and a reference value can be used for retrieval of nutrient profile (e.g. high level of vitamin C in cabbage, moderate level in apple, high level of potassium in banana, and energy density). This suggests applications in the field of dietetics such as healthy food selection as well as recommendation systems for fruit use and in agriculture such as automated sorting and grading, quality control and precision agriculture. Some are still potential uses since they depend upon images of the crops and the comparison of nutrient information to that stored in the system not the actual measurement of nutrient levels. Moreover, the study was carried out on 3 crops and limited number of images (360). Further testing of the model to larger and more varied data sets and more crop varieties in real world conditions in the farm, market and diet is then required and the results of the model compared with the laboratory nutrient analysis. Unless validated, the method will not be useful for food choice and in crop management.

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