Development of a Machine Learning-Based Calorie Estimation Model for Uncooked Nigerian Foods

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Abstract

The assessment of food intake is an important aspect in the promotion of healthy living, particularly in Nigeria, where the challenges that exist in the estimation of the energy value of food consumed have led to the increase of lifestyle diseases such as obesity, diabetes, and heart-related problems. This research aimed at addressing the problem of food estimation through the creation of a machine learning model for the estimation of the calories contained in raw food consumed in Nigeria. The model was developed based on the use of a wide range of food items, 184, which exist in Nigeria. These food items were used, rotated, flipped, and zoomed to improve the accuracy of the model. The CNN algorithm was used for the classification. The accuracy of the model was tested using the Mean Absolute Error, Mean Square Error, and R-square value. The model achieved an R-square value of 0.99. The accuracy of the model was validated based on the existing studies that have been conducted on the estimation of calories through the use of images of food. The model developed can be used for the control of diet for patients on regulated nutrition.

Keywords: Calories estimation, Regional Convolutional Neural Network (R-CNN), Diet management, Image detection, Deep learning

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Introduction

Food is one of the minimal human requirements, providing the calories i.e. energy, required for daily consumption. Misjudged calorie consumption, excess or deficiency, ranks as a world top-listed reason behind many diseases, such as obesity, diabetes, and cardiovascular illnesses, which are widespread in Nigeria. Inability to correctly measure and indicate the quantity of caloric content of food consumed worsens the condition.

Presently, the science of nutritional science has evolved so much and has gained prominence owing to the need to understand what food is, the trend and quantity and quality of food one needs to consume in a single meal per day (Moorhead *et al*., 2015). With nutritional science gaining further pace, how much calorie one consumes from meals, especially self-cooked meals, remains to be monitored precisely. This study sought to seal this loophole by developing a model based on machine learning to estimate calories in raw foods from Nigeria. This is very flexible in the sense that it allows one to adjust portion sizes to fit one's nutritional requirements. By focusing on raw food, the model guarantees structural integrity of the food is maintained, leading to more accurate estimates. The findings can be applied in culinary practice, providing a scientific justification for food consumption and eating habits, and assistance to nutrition practitioners in diet monitoring among patients. The model will simplify the rising occurrence of diet-based diseases by providing an easy and trustworthy measure for diet control. The aim of this study is to develop a model for estimating the calorie content of raw Nigerian foods.

This model will forecast the nutritional content in a portion of food and estimate the calorie content of the dataset that was created from the pictures of raw Nigerian cuisine. The objectives of the study are: to create a dataset with nutritional content for raw Nigerian foods, to develop a machine learning model for caloric estimation using the dataset, and to evaluate the performance of the developed model using standard metrics.

Literature Review

The conventional methods of estimating the calories in food, such as the use of a diary or a barcode scanner, have been found to be inaccurate and time-consuming, owing to the fact that human beings are prone to error. However, the use of deep learning has transformed this field by allowing the use of computer-aided analysis of food images.

The latest research in this field aims to increase the accuracy of the calorie estimation method by addressing the following challenges:

Ingredient and Recipe Recognition: Chen *et al*. (2016) in their study that the recognition of the ingredients used in a dish is more efficient than the recognition of the type of food. By training the deep learning model to simultaneously recognize the ingredients used in the dish and the type of food, it is possible to increase the efficiency of the recipe retrieval system.

Multi-Task Learning: In their study, Ege and Yanai (2017) observed that the use of a deep learning model to simultaneously recognize the type of food, ingredients, and cooking instructions increased the accuracy of the calorie estimation system owing to the interdependencies of these factors.

Novel Detection Methods: Turmchokkasam and Chamnongthai (2018) proposed a system that incorporates thermal imaging and fuzzy logic to detect the components of mixed foods such as soups, where visual detection is challenging.

Portion Size Estimation: The major drawback of the CNN-based approaches is that they did not consider the varying sizes of the food items. Ege *et al*. (2019) proposed novel approaches called DepthCalorieCam and RiceCalorieCam, which make the most precise estimation of the food volume using a stereo camera or a reference object (coin or rice grains).

Localized and Culturally Specific Datasets: Various researchers, such as Ajala *et al*. (2020) and Nnamdi *et al*. (2022), have developed datasets for particular cuisines, such as Nigerian indigenous foods. This has led to high accuracy levels for local cuisine, thereby helping to preserve knowledge about local foods.

Automated Systems and Applications: Deshmukh *et al*. (2021) and Kong *et al*. (2023) have designed systems that take food images as input and automatically determine nutritional values. These systems utilize object detection by Faster R-CNN, object boundaries by Canny edge detection, and reference objects for scale. These systems have been designed for application, ranging from health management to diabetic patients.

Integration with Advanced Models: Cupa (2024) has created a mobile application that uses a "semi-automatic pipeline" with advanced models such as BLIP-2 and GPT-3.5 to accurately identify ingredients, which can be generalized for other cuisines.

The literature search showed that researchers have moved from simple image-to-category classification to more accurate models, including ingredient-level classification, accurate volume estimation, and the use of specialized datasets. However, all researchers have agreed that improvements can be made by increasing the dataset size, using diverse datasets, and fine-tuning models for food characteristics.

Methodology

The design of the machine learning model for the estimation of calories used Convolutional Neural Network, a deep learning technique. A new data set of 184 raw Nigerian foodstuff, i.e., carbohydrates, fats, protein, was created, and the data included images, weights, nutritional values, and approximate calorie values for the foodstuff. The images were obtained from publicly available locations such as Google Images and Kaggle.com. The data set was created with utmost care and attention, keeping in mind the need for data balance for the proper performance of the model, i.e., relating the image with the calorie value of the foodstuff. Data pre-processing included standardization of the data, cleaning of the data, and using data augmentation techniques such as rotation, flip, and zooming of the images for generalization and cleaning of the data. The data was split into training and test data, i.e., 80% and 20%, respectively.

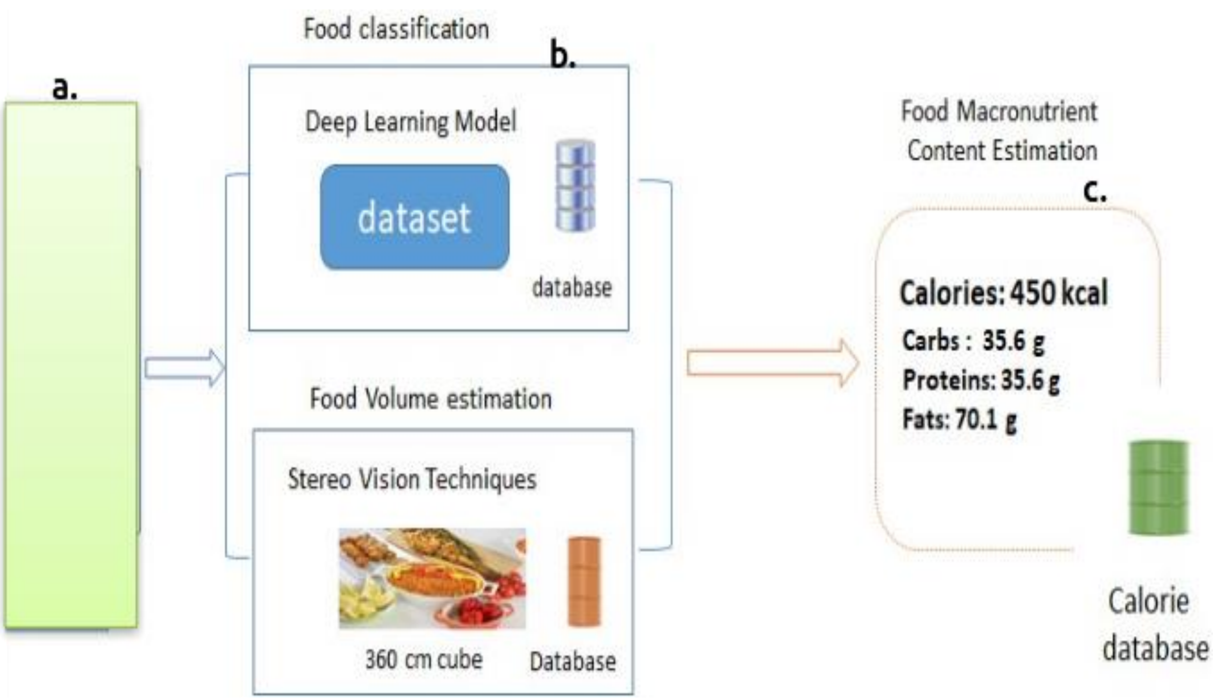


Fig. 1: Architecture of calorie estimation.

The architectural design of the system in Figure 1 consisted of:

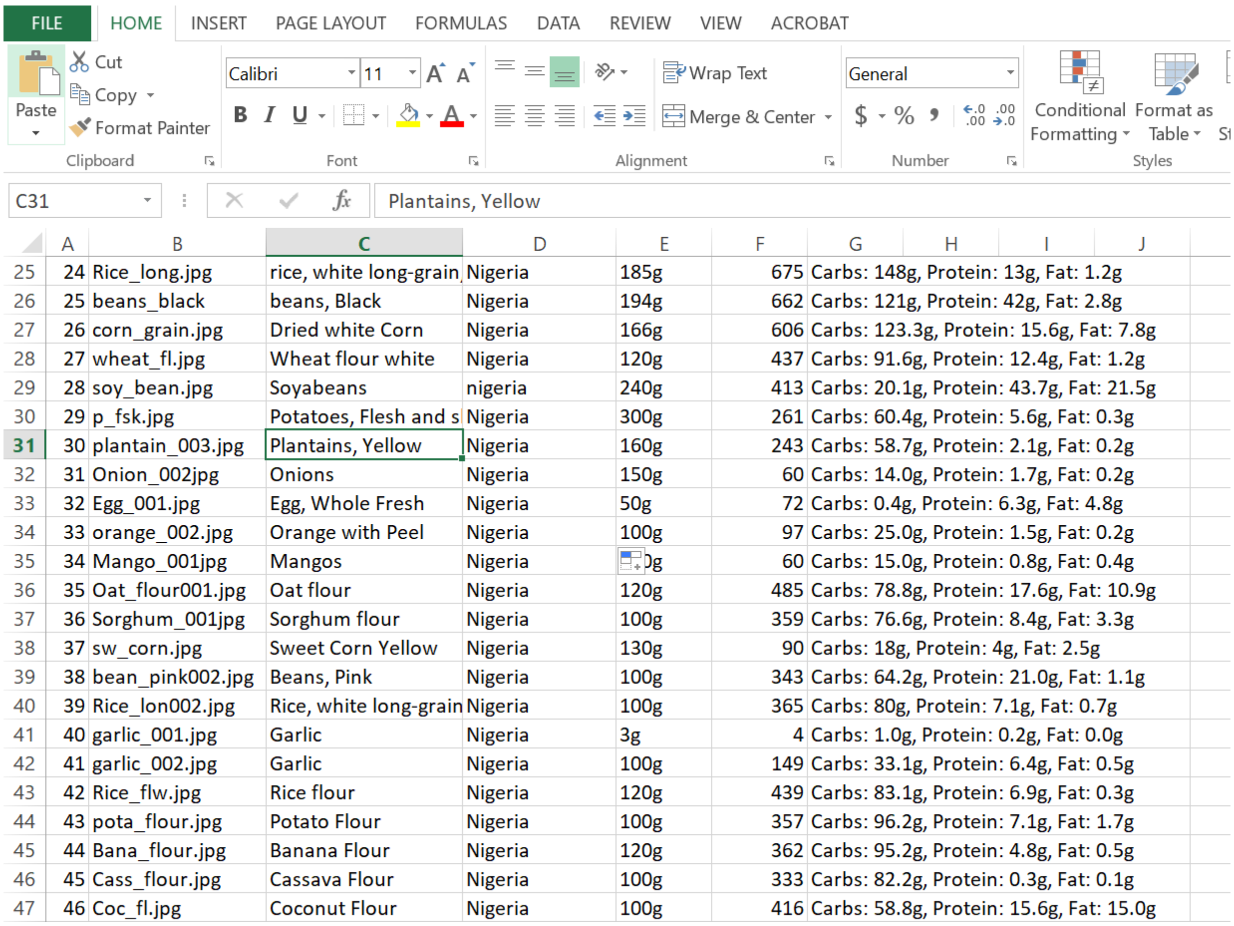
(a) Image Acquisition and Pre-processing: Raw food images are captured and preprocessed to remove noise and standardize format.
(b) Image Detection: The images that are preprocessed have their important features such as volume and nutritional content extracted to be utilized as input to the model.
(c) Calorie Estimation: The model utilizes pre-trained datasets to learn. R-CNN's hidden layers select features and learn patterns within images to predict calorie content based on the information in the database. The model identifies and extracts features, mapping image identity to calorie content from the data set.

The design of the machine learning model for estimation of calories used Convolutional Neural Network, which is a deep learning technique. The model used Regional Convolutional Neural Network, which is effective for image detection and extraction. The implementation of the model is mainly done through Python, which is known for its versatility, readability, and availability of large libraries. TensorFlow, which is a full-featured open-source software library that is considered complete for neural networks, was used for building models. Other tools used include HTML, CSS, JavaScript, which might be used for front-end development, and SQLite, which might be used for backend development.

The model was evaluated based on accuracy, precision, recall, and F1 score.

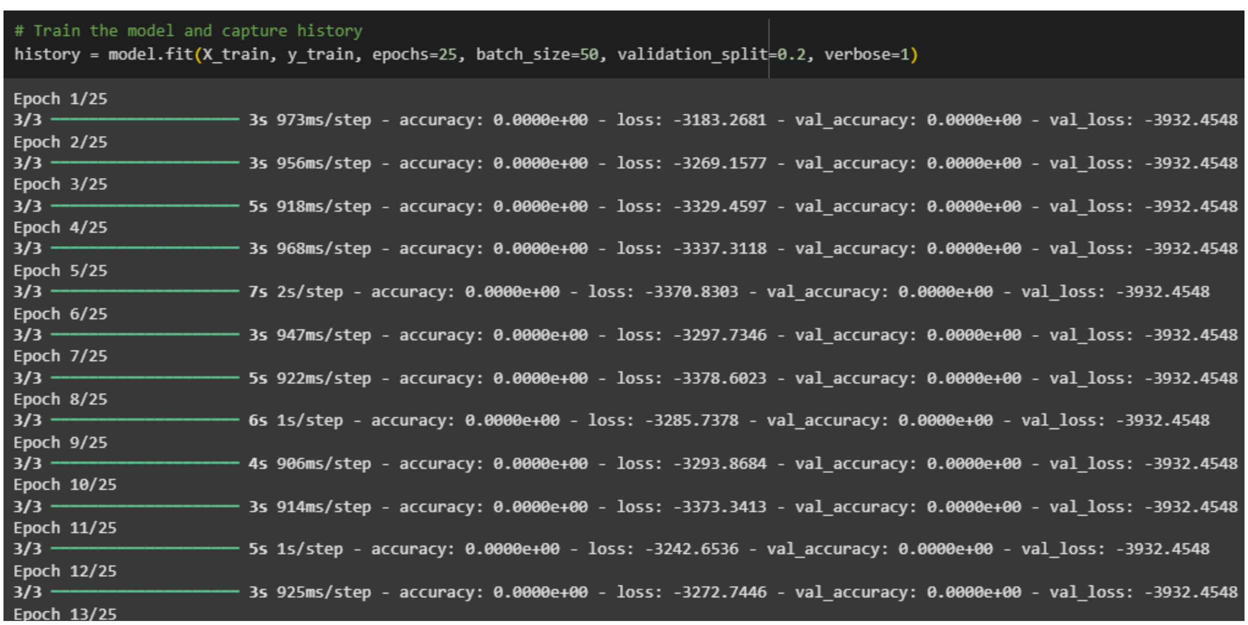
Results and Discussion of Findings

The dataset created in this work is seen in Figure 2.



	A	B	C	D	E	F	G
25	24	Rice_long.jpg	rice, white long-grain,	Nigeria	185g	675	Carbs: 148g, Protein: 13g, Fat: 1.2g
26	25	beans_black	beans, Black	Nigeria	194g	662	Carbs: 121g, Protein: 42g, Fat: 2.8g
27	26	corn_grain.jpg	Dried white Corn	Nigeria	166g	606	Carbs: 123.3g, Protein: 15.6g, Fat: 7.8g
28	27	wheat_fl.jpg	Wheat flour white	Nigeria	120g	437	Carbs: 91.6g, Protein: 12.4g, Fat: 1.2g
29	28	soy_bean.jpg	Soyabeans	nigeria	240g	413	Carbs: 20.1g, Protein: 43.7g, Fat: 21.5g
30	29	p_fsk.jpg	Potatoes, Flesh and s	Nigeria	300g	261	Carbs: 60.4g, Protein: 5.6g, Fat: 0.3g
31	30	plantain_003.jpg	Plantains, Yellow	Nigeria	160g	243	Carbs: 58.7g, Protein: 2.1g, Fat: 0.2g
32	31	Onion_002jpg	Onions	Nigeria	150g	60	Carbs: 14.0g, Protein: 1.7g, Fat: 0.2g
33	32	Egg_001.jpg	Egg, Whole Fresh	Nigeria	50g	72	Carbs: 0.4g, Protein: 6.3g, Fat: 4.8g
34	33	orange_002.jpg	Orange with Peel	Nigeria	100g	97	Carbs: 25.0g, Protein: 1.5g, Fat: 0.2g
35	34	Mango_001jpg	Mangos	Nigeria	0g	60	Carbs: 15.0g, Protein: 0.8g, Fat: 0.4g
36	35	Oat_flour001.jpg	Oat flour	Nigeria	120g	485	Carbs: 78.8g, Protein: 17.6g, Fat: 10.9g
37	36	Sorghum_001jpg	Sorghum flour	Nigeria	100g	359	Carbs: 76.6g, Protein: 8.4g, Fat: 3.3g
38	37	sw_corn.jpg	Sweet Corn Yellow	Nigeria	130g	90	Carbs: 18g, Protein: 4g, Fat: 2.5g
39	38	bean_pink002.jpg	Beans, Pink	Nigeria	100g	343	Carbs: 64.2g, Protein: 21.0g, Fat: 1.1g
40	39	Rice_lon002.jpg	Rice, white long-grain	Nigeria	100g	365	Carbs: 80g, Protein: 7.1g, Fat: 0.7g
41	40	garlic_001.jpg	Garlic	Nigeria	3g	4	Carbs: 1.0g, Protein: 0.2g, Fat: 0.0g
42	41	garlic_002.jpg	Garlic	Nigeria	100g	149	Carbs: 33.1g, Protein: 6.4g, Fat: 0.5g
43	42	Rice_flw.jpg	Rice flour	Nigeria	120g	439	Carbs: 83.1g, Protein: 6.9g, Fat: 0.3g
44	43	pota_flour.jpg	Potato Flour	Nigeria	100g	357	Carbs: 96.2g, Protein: 7.1g, Fat: 1.7g
45	44	Bana_flour.jpg	Banana Flour	Nigeria	120g	362	Carbs: 95.2g, Protein: 4.8g, Fat: 0.5g
46	45	Cass_flour.jpg	Cassava Flour	Nigeria	100g	333	Carbs: 82.2g, Protein: 0.3g, Fat: 0.1g
47	46	Coc_fl.jpg	Coconut Flour	Nigeria	100g	416	Carbs: 58.8g, Protein: 15.6g, Fat: 15.0g

Fig. 2: Database of Uncooked Nigerian food.



```
# Train the model and capture history
history = model.fit(X_train, y_train, epochs=25, batch_size=50, validation_split=0.2, verbose=1)

Epoch 1/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 973ms/step - accuracy: 0.0000e+00 - loss: -3183.2681 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 2/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 956ms/step - accuracy: 0.0000e+00 - loss: -3269.1577 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 3/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 918ms/step - accuracy: 0.0000e+00 - loss: -3329.4597 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 4/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 968ms/step - accuracy: 0.0000e+00 - loss: -3337.3118 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 5/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 7s 2s/step - accuracy: 0.0000e+00 - loss: -3370.8303 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 6/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 947ms/step - accuracy: 0.0000e+00 - loss: -3297.7346 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 7/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 922ms/step - accuracy: 0.0000e+00 - loss: -3378.6023 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 8/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 6s 1s/step - accuracy: 0.0000e+00 - loss: -3285.7378 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 9/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 906ms/step - accuracy: 0.0000e+00 - loss: -3293.8684 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 10/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 914ms/step - accuracy: 0.0000e+00 - loss: -3373.3413 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 11/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.0000e+00 - loss: -3242.6536 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 12/25
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 925ms/step - accuracy: 0.0000e+00 - loss: -3272.7446 - val_accuracy: 0.0000e+00 - val_loss: -3932.4548
Epoch 13/25
```

Fig. 3: Screenshot of training and validation of RCNN model.

The accuracy, valaidation accuracy and validation loss are presented in Figure 3 as the model is executed for calorie estimation during training and testing. The values show consistency over the iteration.

Table 1: Results of Performance Evaluation Metrics

Metric	Value	Interpretation	Implication
Mean Absolute Error (MAE)	14.46	Average absolute difference between actual and predicted values.	Model predictions are off by 14.46 units on average.
Mean Squared Error (MSE)	315.24	Average squared differences between actual and predicted values.	Higher weight on larger errors suggests that some large deviations exist.
Root Mean Squared Error (RMSE)	17.78	Square root of MSE, giving error in original units.	Errors are about 17.78 units on average; more sensitive to large errors.
R-Square (R^2)	0.99	Percentage of variance explained by the model.	99% of the variance is explained, suggesting a very strong fit but potential overfitting.

In Table 1, the developed model achieved an R-square score of 0.99, indicating a high level of accuracy and precision in estimating calorie content from uncooked Nigerian food images. While minor errors were observed, such as a 23.35% mean square error for calorie estimation of soybeans, the overall performance demonstrated the model's effectiveness and efficiency. The scatter plots and MAE/Loss graphs visually confirmed the model's robust performance.

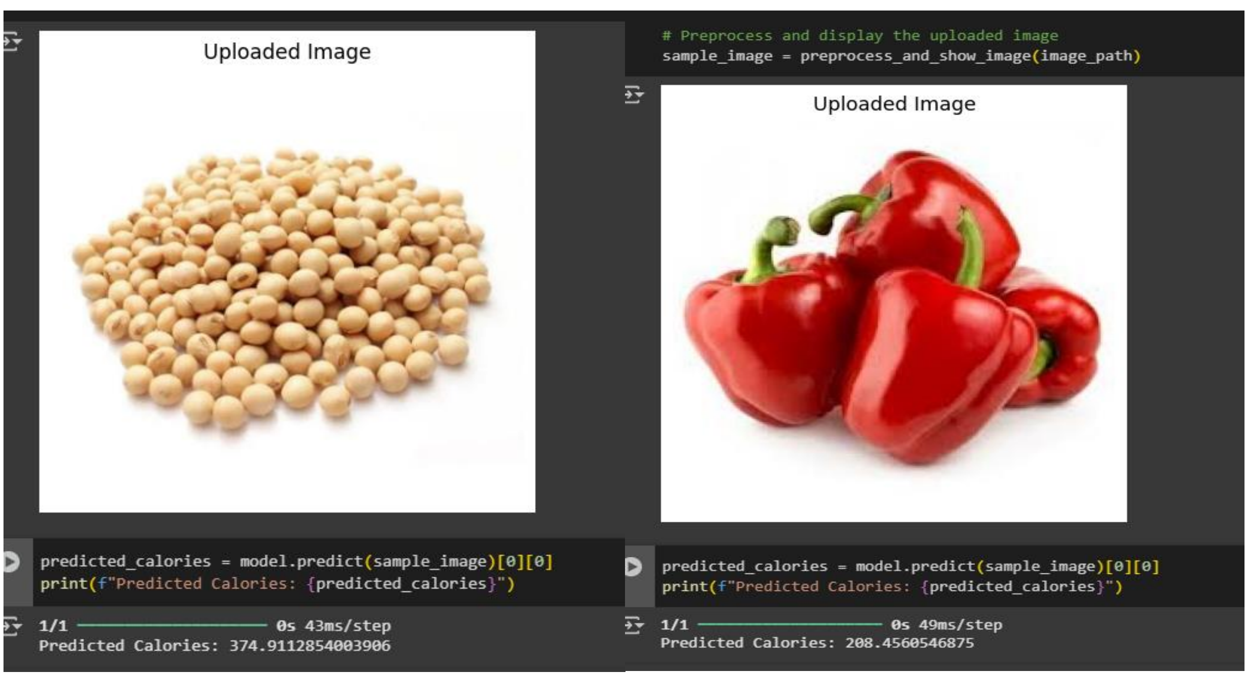


Fig. 4: Raw Food with predicted calories using the model.

The Calorie Estimation model was tested on some raw foods available and the predicted results are shown in Figure 4. The predicted calories for the first food is 374 and 208 for the bell peppers. The work of Cupa (2024) is similar to this but it was done using cooked Korean food.

Discussion of Findings

The size and the fitness of a dataset are critical roles in determining the level of accuracy and precision of any model. The large dataset provided the model with a wide range of learning and capability to study the pattern, allowing it to learn and perform accurately. It was observed from the experiment that the level of accuracy increased with an increase in the number of datasets. The findings show that when the number of the dataset was increased, the model's performance also increased, leading to a significant improvement. Ajala *et al*. (2020) also created a Nigerian dataset for their work.

The developed model performance was evaluated on a test dataset, and its performance was measured using appropriate metrics. The accuracy score provides an overall measure of correctness, while the classification report gives insight into Mean Square error, mean absolute error, Root mean square error and the R-square score. Due to the limited number of datasets. The scatter plots of residuals versus predicted values to check for homoscedasticity (constant variance of residuals), model diagnostics, and features selection provide a clear visual overview of relationships, trends, and potential problems in the data. As it can be observed from the graph, the visualizing trend and pattern are linear between the variables.

The mean square error is 315.24, which is the average of the square difference between the actual and the predicted values is 315.24. This indicates that, on average, the square of the difference between the predicted and actual values is 315.24. It shows how far off the predictions are, it is noted that a higher value generally indicates a poor model fit. The value is better because of the fewer datasets used for the model. The root mean square error (RMSE) is the square root of MSE, so the value of RMSE is 17.78. The implication of this is that for every prediction of the model, there is an off by about 17.78 units of whatever the target variable is. The mean square error is used as a loss function in regression models. A lower MSE indicates a better fit, meaning the model makes smaller errors on average.

The mean absolute error (MAE) measures the average absolute difference between actual and predicted values in a regression model. The value of MAE is 14.46, meaning that, on average, the model's predictions are off by 14.46 units in absolute terms. The value of MAE is a small fraction of the target variable's range showing that the model is performing, and the value is acceptable due to the fewer datasets. The improvement is achieved by handling the outlier and hyperparameter tuning.

R-Square Score: An R2 value close to 1.0 means the model explains nearly all the variance in the data. The value suggests an excellent fit, meaning that all predictions are highly aligned with actual value. However, this may also suggest traces of error in the performance of the model. The architecture of the Calorie Estimation model is similar to that proposed by Deshmukh *et al*. (2021).

Conclusion

This study was successful in developing and evaluating a machine learning-based approach for calorie estimation of uncooked Nigerian foods using Regional Convolutional Neural Networks. This study also provided a tool for calorie management, thereby addressing chronic health issues such as obesity and diabetes, which are common in Nigeria. The use of uncooked ingredients in the development of the model ensured the availability of constant and accurate data, resulting in a high level of accuracy and precision. This study also confirms the importance of technological innovation in ensuring a healthy lifestyle by providing accurate dietary management tools. Therefore, it is strongly recommended that a more robust and comprehensive dataset of uncooked Nigerian foods be developed to further improve the efficacy, robustness, and accuracy of the model developed in this study. The use of more advanced neural network architectures may also optimize the size and accuracy of the model for classification purposes. The inclusion of more metadata, such as the weights of the food items, will also improve the accuracy of the dietary management tools.

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