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HiwApp: Preliminary Results for an Android Application Culinary Tool Identifying Meat Cuts Using Machine Learning

Jessa Marie Nolido Añana[1], Nelia Quilicot Catayas[1], Max Angelo Dapitilla Perin[2], Darrel Abuyabor Cardaña[2] and Cecilia Tabel Gumanoy[2]

[1] Industrial Technology Department, Bohol Island State University-Bilar Campus, Bohol, Philippines
[2]Computer Science Department, Bohol Island State University-Bilar Campus, Bohol, Philippines

E-mail address: jessamarie.anana@bisu.edu.ph, nelia.catayas@bisu.edu.ph, maxangelo.perin@bisu.edu.ph, darrel.cardana@bisu.edu.ph, cecilia.gumanoy@bisu.edu.ph

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Abstract: Technological advancements are reshaping the culinary landscape, aiming to improve cooking processes and dining experiences. The integration of machine learning into culinary tools, including meat cut identification, is gaining traction globally. In the Philippines, where culinary heritage is rich and diverse, technology increasingly finds its place in kitchens. Despite this, identifying meat cuts remains challenging, prompting innovative technological solutions. Bohol, a province in the Philippines, reflects this trend, with a growing interest in modern culinary tools among local chefs and home cooks. In this context, the development of HiwApp, an Android application utilizing machine learning for meat cut identification, represents a notable advancement. HiwApp employs supervised machine learning, specifically the k-Nearest Neighbors (k-NN) algorithm, to identify meat cuts that cater to professional chefs and home cooks. This paper introduces HiwApp's development process, detailing its methodology, which includes synthetic data augmentation, algorithm implementation, and user interface design. Preliminary results indicate HiwApp's satisfactory performance, achieving an 84.55% accuracy rate. Future efforts aim to address limitations and enhance HiwApp's meat cut recognition capabilities, improving user culinary experiences. Additionally, recommendations for future development include predicting dishes based on identified cuts, estimating market income, and integrating features for recipe suggestions and freshness prediction to broaden HiwApp's practical applications.

Keywords: Meat Cut, API, Mobile Application, Food

1. Introduction

The culinary world has always been dynamic, adapting to new technologies and innovations that enhance the cooking process and the dining experience. Globally, the demand for precision and expertise in food preparation has led to the development of numerous tools and applications designed to assist chefs and home cooks alike. One significant advancement in this field is integrating machine learning with culinary tools, enabling the identification and utilization of various ingredients, including meat cuts.

In the Philippines, a nation known for its rich culinary heritage and diverse food culture, the application of technology in the kitchen is increasingly becoming a norm. With its unique blend of flavors and techniques, Filipino cuisine often relies on specific meat cuts to achieve authentic dishes. However, accurately identifying these cuts can be challenging for many, particularly those who must be professionally trained. This has paved the way for innovative solutions that leverage technology to simplify this aspect of cooking.

Bohol, an island province in the Central Visayas region of the Philippines, is no exception to this trend. Known for its agricultural produce and vibrant culinary scene, Bohol has seen a growing interest in modern culinary tools. The local chefs and home cooks are constantly seeking ways to improve their skills and knowledge, particularly in preparing meat dishes, a staple in many Boholano celebrations and daily meals.

In this context, the development of HiwApp, an Android application designed as a culinary tool for identifying meat cuts using machine learning, represents a significant leap forward. By utilizing advanced algorithms

E-mail: jessamarie.anana@bisu.edu.ph, nelia.catayas@bisu.edu.ph, maxangelo.perin@bisu.edu.ph, darrel.cardana@bisu.edu.ph, cecilia.gumanoy@bisu.edu.ph

and image recognition technology, HiwApp aims to assist users in accurately identifying various meat cuts, thus enhancing their cooking experience and ensuring the authenticity of their dishes. Figure 1 provides a comprehensive list of the meat cuts referenced from Virginia Boys Kitchens [9].

Identifying and classifying meat cuts has become increasingly challenging, especially given the variety of cuts and their specific uses in culinary practices. The proposed study introduces HiwApp, an innovative Android application designed to identify meat cuts using the k-Nearest Neighbors (k-NN) algorithm to address this challenge. This approach incorporates a machine learning algorithm for image recognition, precise classification using k-NN, and a comprehensive database for validation. HiwApp aims to assist users in accurately identifying various meat cuts, thus enhancing their cooking experience and ensuring the authenticity of their dishes.

In response to the growing demand for accurate meat cut identification, there has been a surge in research focusing on machine learning applications in this domain. One notable contribution comes from Prakash et al. [1], who used artificial intelligence to automate meat cut identification from the semimembranosus muscle on beef boning lines, achieving significant success in precision and accuracy. Hwang et al. [2] developed a hybrid image processing technique for robust extraction of lean tissue on beef cut surfaces, demonstrating the potential of combining different image processing methods. Sinanoglou et al. [3] assessed the quality of pork and turkey hams using FT-IR spectroscopy, colorimetric, and image analysis, showcasing the versatility of image analysis techniques in meat quality assessment. GC et al. [4] employed deep learning neural networks to classify beef cuts, highlighting the advancements in artificial intelligence technology for meat classification.

While researchers have widely employed neural networks for meat cut recognition tasks, other studies have showcased the adaptability and effectiveness of the k-NN algorithm. One notable work is the EskayApp developed by Perin, Feliscuzo, and Sta. Romana [5] employs the k-NN algorithm in a mobile application. The study achieved an accuracy rate of 89.93% based on a 2x2 confusion matrix. This groundbreaking study is pioneering in optical character recognition (OCR) and e-learning applications tailored explicitly for the Eskaya script, establishing a solid foundation for future research endeavors focusing on OCR for specific scripts.

Additional studies have demonstrated the versatility of the k-NN algorithm in various domains. Perin, Cardaña, and Gumanoy [6] developed eBaybayMo, an e-learning mobile application tool for transliterating Baybayin characters to Latin letters, achieving notable accuracy. Another study by Cardaña et al. [7] introduced StenogrApp, an e-learning Android application for recognizing basic Gregg Shorthand using machine learning, further highlighting the effectiveness of the k-NN algorithm in educational technology.

Ghosh, Bora, Das, and Chaudhuri [8] modified an Assamese OCR system to accommodate the Bangla language, which shares visual similarities. This adaptation achieved an accuracy rate of approximately 97% when tested on 1800 printed document pages.

In the context of meat cut recognition, the application of the k-NN algorithm has been relatively limited, representing a potential research gap in this field. The development of HiwApp represents a significant leap forward in the culinary field, leveraging the k-NN algorithm to ensure high accuracy and reliability, making it a valuable tool for both professional chefs and home cooks.

A. Objective

The primary objective of this research is to develop a mobile e-learning application for meat cut recognition using the k-NN algorithm. The focus is on creating an intelligent system that identifies various meat cuts. By utilizing supervised machine learning and the k-NN algorithm, the application will provide a method for meat cut identification. This research aims to enhance the culinary experience for users by ensuring meat cut recognition, contributing to more cooking practices, and better utilization of meat cuts in various dishes. Additionally, this study seeks to establish a foundation for further advancements in the application of machine learning in culinary tools and technologies.

2. METHODS

The developmental research focused on implementing the k-NN Algorithm within the project's business logic layer or backend. Supervised Machine Learning techniques were integrated to construct an application programming interface (API). This API facilitates the seamless capture of images of meat cuts through camera access and accurately recognizes the type of meat cut to meet the requirements of the Presentation Layer. Figure 2 provides a visual representation of the project's diagram, while this section delves into the comprehensive exploration of the research methodology.

A. Data Access Layer

The initial seed data size within the Data Access Layer (DAL) context is notably limited. To address this constraint and optimize algorithms, particularly those like k-NN, that benefit from larger datasets, a crucial technique is employed: algorithmic generation of synthetic data. This augmentation process plays a pivotal role in enhancing the performance of our DAL.

The study utilizes a specific approach to augment the dataset's size and diversity. This method involves subjecting the 12 meat cuts to transformations. Initially, each meat cut undergoes mirroring, followed by incremental rotations, with each rotation precisely 1 degree, spanning a complete 360-degree rotation, as illustrated in Figure 3. This process yields an entirely new dataset comprising 4,320 images. Enriching the dataset in this manner significantly enhances the diversity and richness of the training data, thereby benefiting both the data access layer and the underlying model.

$$\begin{aligned} New\ training\ set &= 12\ (Original\ set) * 360\ (rotation) \\ &= 4320\ images \end{aligned}$$

Incorporating synthetic data into the training process, the model becomes more robust and capable of handling unexpected inputs, thereby increasing its accuracy in classifying meat cut images.

B. Business Logic Layer

The project application employed the k-Nearest Neighbors (k-NN) algorithm in its backend, utilizing supervised machine learning techniques to develop the application programming interface (API). This approach is particularly efficient for transliteration tasks due to its simplicity and effectiveness. To assess the algorithm's performance accurately, the project involves constructing a supervised machine-learning model specifically for the transliteration task using the k-Nearest Neighbors (k-NN) algorithm. The model's performance is evaluated using a 12x12 confusion matrix, which is instrumental in calculating accuracy and other performance metrics.

Python was chosen as the server-side programming language for this implementation due to its user-friendly nature and concise syntax. These attributes of Python significantly expedite the development process, allowing for swift and efficient algorithm evaluation before immediate implementation. Python's extensive libraries and tools for machine learning, such as NumPy and sci-kit-learn, further facilitated the seamless integration and testing of the k-NN algorithm.

Before feature extraction, the images undergo several preprocessing techniques to enhance the quality and accuracy of the extracted features. These preprocessing steps include Gaussian filtering, thresholding, median filtering, image resizing, and image inversion. Each technique serves a specific purpose in preparing the images for accurate feature extraction. For instance, Gaussian filtering helps reduce image noise, while thresholding converts grayscale images into binary images, simplifying the subsequent processing steps. Median filtering further reduces salt-and-pepper noise, which is common in scanned documents. Image resizing ensures that all images have a uniform size, facilitating consistent feature extraction. Lastly, image inversion is applied to standardize the background and foreground, making the features more prominent.

The contour feature extraction technique, also known as boundary following or contour tracing, is employed to delineate the boundary of the images. By tracing an ordered sequence of boundary pixels, the system effectively identifies and eliminates irrelevant features that might be present in the characters within the photograph. Proper contour tracing is crucial as it enhances the recognition system's performance by delivering highly accurate features essential for the classification process.

The k-Nearest Neighbors technique is the classification algorithm due to its robustness and simplicity. In the k-NN approach, the value of k dictates the number of neighbors considered for classification. Interestingly, it has been observed that variations in the k value do not significantly impact the recognition rate, indicating the algorithm's stability. In this approach, the distance between the features of each test image and the training images is computed, and the test image is classified based on the majority class of its k nearest neighbors.

The training data for the model comprises feature vectors, which are stored in a .npy file. This format efficiently stores large arrays of numerical data, making it ideal for training the k-NN model. The feature vectors train the k-NN model, enabling it to accurately classify new images based on the learned features.

The success of this project application lies in the combination of effective preprocessing techniques, robust feature extraction, and the k-NN algorithm. The preprocessing steps ensure the quality and consistency of the images, while contour tracing delivers precise features necessary for classification. The k-NN algorithm, with its stability and simplicity, provides a reliable method for transliteration tasks. By leveraging Python's powerful libraries and tools, the development and implementation of the algorithm are streamlined, resulting in a high-performing and accurate transliteration system.

C. Presentation Layer

The Presentation Layer of the meat cut classification system is pivotal in developing a user-friendly mobile application that effectively communicates identified meat cuts to users. This layer focuses on creating an intuitive and visually appealing interface that enhances user interaction and satisfaction. Central to this effort is the choice of C# as the programming language, selected for its robust features and cross-platform compatibility, which ensures the application's usability across various mobile devices and operating systems. C# facilitates the development of responsive user interfaces that streamline the capture and display of meat cut identification results. The choice of C# supports efficient application performance and enables future scalability with potential enhancements in visualization techniques, multilingual support, and advanced user analytics. These developments aim to elevate the application's utility in culinary practices, educational contexts, and beyond, ensuring it remains adaptable and responsive to evolving user needs and technological advancements.

3. RESULTS AND DISCUSSION

A dedicated software application is essential to thoroughly assess the accuracy and performance of the MeatCut API. To achieve this, the API was integrated into a mobile application specifically developed for this study, named HiwApp. This integration allowed for a practical and user-friendly platform to test the API in real-world scenarios. By embedding the API into HiwApp, researchers could streamline the process of capturing images of meat cuts, processing these images through the k-Nearest Neighbors (k-NN) algorithm, and displaying the resulting classifications directly to users. Figure 4 illustrates the interface and functionality of HiwApp, highlighting how users interact with the application to input images and receive immediate feedback on the identified meat cuts. This mobile application served as a tool for rigorous testing and evaluation of the API's accuracy and provided a practical demonstration of how the technology could be utilized in everyday culinary settings. Through extensive testing facilitated by HiwApp, researchers gathered comprehensive data on the API's performance, identified improvement areas, and ensured the system's robustness and reliability before broader deployment.

A. Accuracy

Accuracy serves as one of the metrics used to evaluate classification models. Informally, accuracy measures the proportion of correct predictions made by the model. Formally, accuracy is defined as follows:

Accuracy = (Number of correct predictions)/(Total number of predictions)

The researcher tested the mobile application to measure the accuracy of the API. The researchers rotated to increase the sample pictures when capturing 12 meat cut images, as shown in Figure 5.

Number of pictures tested = (12 meat cuts characters x 10 different sides)

Thus, the total number of test images was n = 120.

The initial analysis of test images revealed instances of empty results. Figure 6 presents the outcomes of the data-gathering process. Upon applying the formula for 12x12 matrix classification, the model achieved an accuracy rate of 84.55%. While this figure initially suggests high performance, a closer examination of the confusion matrix provides a more nuanced understanding of the model's accuracy.

B. Precision, Recall, F1 Score, and Specificity

The detailed calculations for precision, recall, F1 score, and specificity for each meat cut are as follows.

For Rib Eye Steak, the model identified 2 True Positives (TP), meaning it correctly recognized two instances of Rib Eye Steak. However, the model produced no False Negatives (FN), indicating it did not miss any actual Rib Eye Steak instances. Despite this, the model generated 10 False Positives (FP), incorrectly classifying other cuts as Rib Eye Steak. There were 108 True Negatives (TN) correctly identified instances that were not Rib Eye Steak. This result highlights the model's difficulty in accurately distinguishing Rib Eye Steak from similar cuts, resulting in many misclassifications.

The Rib Steak classification showed perfect performance. The model identified 10 True Positives (TP), correctly recognizing all instances of Rib Steak. No false negatives (FN) indicated no rib steak instances were missed. Additionally, there were no False Positives (FP), meaning no other cuts were mistakenly classified as Rib Steak. The model had 110 True Negatives (TN), correctly identifying all non-Rib Steak cuts. This perfect classification demonstrates the model's ability to recognize Rib Steak accurately.

Similar to Rib Steak, the T-Bone Steak category also exhibited flawless performance. The model produced 10 True Positives (TP), correctly identifying all T-Bone Steak instances, with no False Negatives (FN). Additionally, there were no False Positives (FP), ensuring no misclassifications. The model achieved 110 True Negatives (TN), correctly classifying all non-T-Bone Steak cuts. This indicates the model's robustness in recognizing T-Bone Steak accurately.

The Tri-tip Roast category followed the same trend of high accuracy. The model identified 10 True Positives (TP), with no False Negatives (FN) and no False Positives (FP). It also achieved 110 True Negatives (TN). This consistent performance across these categories reflects the model's strong capability to identify Tri-tip Roast accurately and reliably.

For Rump Cap, the model identified 6 True Positives (TP), correctly recognizing six instances of Rump Cap. However, there were 4 False Negatives (FN), where the model failed to identify actual Rump Cap instances. There were no False Positives (FP), ensuring no other cuts were misclassified as Rump Cap and 110 True Negatives (TN). This result suggests a need for improvement in the model's ability to detect Rump Cap, given the higher rate of missed instances.

The Round Cut classification showed 8 True Positives (TP), correctly identifying eight instances, with 2 False Negatives (FN), indicating some missed instances. There were 2 False Positives (FP), where other cuts were incorrectly classified as Round Cut, and 108 True Negatives (TN). These results reflect moderate accuracy, with room for enhancement in reducing misclassifications and missed detections.

The Shank Meat category displayed perfect performance with 10 True Positives (TP), no False Negatives (FN), and no False Positives (FP). The model achieved 110 True Negatives (TN). This high accuracy demonstrates the model's effectiveness in reliably identifying Shank Meat.

Flank Steak also achieved perfect classification with 10 True Positives (TP), no False Negatives (FN), and no False Positives (FP), along with 110 True Negatives (TN). This consistency underscores the model's robustness in recognizing Flank Steak accurately.

The Short Plate Primal category showed 4 True Positives (TP), correctly identifying four instances, but there were 6 False Negatives (FN), indicating several missed instances. There were no False Positives (FP), ensuring no other cuts were misclassified as Short Plate Primal and 110 True Negatives (TN). This result indicates a need for improvement in accurately detecting Short Plate Primal.

For Foreshank, the model identified 3 True Positives (TP), correctly recognizing 3 instances, but it had 7 False Negatives (FN), showing many missed instances. No False Positives (FP) and 110 True Negatives (TN) existed. This indicates considerable challenges in accurately identifying Foreshank, necessitating further refinement.

The Brisket Cut classification was perfect, with 10 True Positives (TP), no False Negatives (FN), and no False Positives (FP). The model had 110 True Negatives (TN), reflecting vital accuracy and reliability in identifying Brisket Cut.

Lastly, Beef Chuck also demonstrated perfect performance with 10 True Positives (TP), no False Negatives (FN), no False Positives (FP), and 110 True Negatives (TN). This result indicates the model's robust capability in accurately recognizing Beef Chuck.

Overall, the model displayed high accuracy in several meat cut categories, including Rib Steak, T-Bone Steak, Tri-tip Roast, Shank Meat, Flank Steak, Brisket Cut, and Beef Chuck. However, it faced challenges with Rib Eye Steak, Rump Cap, Round Cut, Short Plate Primal, and Foreshank, highlighting areas where further refinement and additional training data may be needed to improve performance and reduce misclassifications. This detailed analysis of individual meat cuts provides valuable insights into the model's strengths and areas for improvement, guiding future efforts to enhance the MeatCut API's accuracy and reliability.Summary of Performance Metrics

The overall performance metrics for the meat cut classification model are summarized in Table 1.

TABLE I. SUMMARY OF THE PERFORMANCE METRICS

Meat Cuts	*Precision*	*Recall*	*F1 Score*	*Specificity*
Rib Eye Steak	16.7%	**100%**	**28.6%**	**91.5%**
Rib Steak	100%	**100%**	**100%**	**100%**
T-Bone Steak	100%	**100%**	**100%**	**100%**
Tri-tip Roast	100%	**100%**	**100%**	**100%**
Rump Cap	100%	**60%**	**75%**	**100%**
Round Cut	80%	**80%**	**80%**	**98.2%**
Shank Meat	100%	**100%**	**100%**	**100%**
Flank Steak	100%	**100%**	**100%**	**100%**
Short Plate Primal	100%	**40%**	**57%**	**100%**
Foreshank	100%	**30%**	**46%**	**100%**
Brisket Cut	100%	**100%**	**100%**	**100%**
Beef Chuck	100%	**100%**	**100%**	**100%**

The evaluation of the meat cut classification model developed using the HiwApp application reveals varied performance metrics across different types of meat cuts. Precision, which measures the model's accuracy in correctly predicting positive instances among all optimistic predictions, ranged significantly among the cuts. Cuts such as Rib Steak, T-Bone Steak, Tri-tip Roast, Shank Meat, Flank Steak, Brisket Cut, and Beef Chuck achieved perfect precision scores of 100%, indicating flawless identification without any false positives. This precision is crucial for culinary applications where accuracy in identifying specific cuts directly impacts cooking techniques and dish preparation. However, some cuts exhibited lower precision scores, notably Rib Eye Steak, with 16.7%, indicating challenges in distinguishing visually similar cuts accurately. Conversely, cuts like Short Plate Primal and Foreshank achieved 100% precision, showcasing the model's capability to differentiate these cuts from others in the dataset accurately.

Regarding recall, which measures the model's sensitivity in identifying all actual positive instances among predicted positive instances, the model demonstrated strong performance across several cuts. Cuts such as Rib Steak, T-Bone Steak, Tri-tip Roast, Shank Meat, Flank Steak, Brisket Cut, and Beef Chuck achieved perfect recall scores of 100%, indicating comprehensive identification of all instances of these cuts without any misses. This high recall underscores the model's effectiveness in recognizing these cuts reliably, which is essential for ensuring consistent culinary outcomes and operational efficiency. However, cuts like Rump Caps and Round Cuts showed variability in recall scores, suggesting opportunities for improvement in detecting all instances of these cuts accurately.

The F1 score balances precision and recall into a single metric, providing a holistic view of the model's overall performance. Cuts with high F1 scores, such as Rib Steak, T-Bone Steak, Tri-tip Roast, Shank Meat, Flank Steak, Brisket Cut, and Beef Chuck, achieved perfect scores of 100%, indicating robust performance in both precision and recall. This balanced performance is crucial for maintaining consistency and accuracy in meat cut identification, supporting efficient culinary operations, and recipe execution. Conversely, cuts like Rib Eye Steak and Rump Cap demonstrated lower F1 scores, highlighting challenges in achieving a balance between precision and recall for these specific cuts.

Lastly, specificity, which measures the model's ability to identify negative instances among all actual negative instances correctly, showed high performance across many cuts. Cuts such as Rib Steak, T-Bone Steak, Tri-tip Roast, Shank Meat, Flank Steak, Brisket Cut, and Beef Chuck achieved perfect specificity scores of 100%, indicating accurate identification of non-target cuts and minimal false positives. However, cuts like Rib Eye Steak and Round Cut demonstrated slightly lower specificity scores, suggesting instances where the model incorrectly identified other cuts as these specific types.

While the meat cut classification model developed using HiwApp demonstrates significant strengths in precision, recall, F1 score, and specificity for many cuts, there are notable variations across different meat cuts. These results highlight the model's capabilities and areas for improvement, particularly in enhancing accuracy in distinguishing visually similar cuts and achieving consistency across all categories. Continued model refinement through algorithm optimization and dataset expansion will be crucial for advancing its effectiveness in real-world culinary applications, ensuring precise and reliable meat cut identification to support culinary innovation and operational excellence.

4. CONCLUSION AND RECOMMENDATIONS

The primary aim of this study was to develop an intelligent API using the k-Nearest Neighbors (k-NN) algorithm to identify meat cuts accurately. The model demonstrated satisfactory performance, achieving an impressive accuracy rate of 84.55%. However, the current API is tailored primarily for simple meat cuts. It was trained using printed images, potentially limiting its recognition capability in real-world scenarios with varied conditions and meat types. This limitation restricts the API's utility and underscores the need for further enhancements.

Discussion of precision, recall, F1 score, and specificity metrics revealed significant insights into the model's performance across different meat cuts. Cuts such as Rib Steak, T-Bone Steak, Tri-tip Roast, Shank Meat, Flank Steak, Brisket Cut, and Beef Chuck exhibited high precision and recall scores, indicating robust accuracy in identifying these cuts accurately and consistently. Conversely, cuts like Rib Eye Steak showed challenges in precision, highlighting the need for improved differentiation among visually similar cuts. These findings underscore the importance of refining the model's algorithms and expanding its training dataset to enhance performance across all meat types and conditions.

Several recommendations aim to enhance the API's capabilities and practical applications. Firstly, integrating predictive features to recommend dishes based on identified meat cuts can significantly enhance user experience and engagement. Such functionalities cater to culinary enthusiasts and provide valuable insights into market trends and consumer preferences in the meat industry. Moreover, incorporating algorithms to predict meat freshness can bolster food safety measures, ensuring quality assurance in food processing and distribution.

Action research utilizing the mobile application and statistical analyses like t-tests to compare educational outcomes across different user groups can provide empirical evidence of the API's educational impact. Furthermore, adding a comprehensive database of Filipino dishes with clickable links to their ingredients can cater specifically to local culinary preferences, enhancing user engagement and practical utility in diverse cultural contexts.

In conclusion, while the current API demonstrates promising performance in meat cut identification, ongoing efforts to enhance its robustness and versatility are essential. By addressing current limitations and implementing recommended enhancements, the API can become a more powerful tool for culinary professionals, educators, and consumers, contributing to advancements in culinary arts and food technology domains. These efforts aim to broaden the API's scope and maximize its value in various real-world applications, ensuring its relevance and effectiveness in dynamic culinary environments.

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Jessa Nolido Anaña is a faculty member in the Industrial Technology Department within the College of Technology and Allied Sciences at Bohol Island State University-Bilar Campus. She earned her bachelor's degree in Food Technology and a Master of Science in Food Science & Technology, with a minor in Horticulture, from Visayas State University-Main Campus in Baybay City, Leyte. Her research interests include food innovation and development, microbial and chemical evaluation of food, and the optimization of food products. She can be contacted via email: jessamarie.anana@bisu.edu.ph

Nelia Quilicot Catayas is a faculty member and currently the Dean of the College of Technology and Allied Sciences, working closely with two departments, Industrial Technology and Computer Science. She earned her baccalaureate degree, Bachelor of Science in Education, majoring in Technology and Livelihood Education at Bohol Island State University Bilar Campus and pursued her Master of Arts in Teaching Vocational Education at Bohol Island State University-Main Campus at Tagbilaran City, Bohol, and her doctoral degree at Cebu Technological University, Main Campus, Cebu City. She is interested in food processing, food innovation, and development. She can be contacted at nelia.catayas@bisu.edu.ph.

Max Angelo Dapitilla Perin is a faculty member in the Computer Science Department at the College of Technology and Allied Sciences, Bohol Island State University-Bilar Campus. He earned his bachelor's degree in computer engineering from Bohol Island State University-Main Campus and a master's degree in computer science from Cebu Institute of Technology-University. He is pursuing a Doctorate in Information Technology at Cebu Institute of Technology-University. His research interests include full-stack development, machine learning, and computational linguistics. He can be contacted via email at maxangelo.perin@bisu.edu.ph.

Darrel Abuyabor Cardaña is a faculty member in the Computer Science Department at the College of Technology and Allied Sciences, Bohol Island State University-Bilar Campus. He holds a master's degree in information systems from Lorma Colleges San Juan Campus. He is pursuing a Ph.D. in Technology Management at Cebu Technological University – Main Campus, Cebu City, Cebu. His research interests encompass applied machine learning, information systems, and sustainability. He can be contacted via email at darrel.cardana@bisu.edu.ph.

Cecilia Tabel Gumanoy is a faculty member in the Computer Science Department at the College of Technology and Allied Sciences, Bohol Island State University-Bilar Campus. She earned her bachelor's degree in computer engineering from Holy Name University. She is pursuing a Masters in Information Systems at Lorma Colleges San Juan Campus. Her research interests include data science and natural language processing. She can be contacted via email at cecilia.gumanoy@bisu.edu.ph.

Figure 1. Meat Cuts from Virginia Boys Kitchen

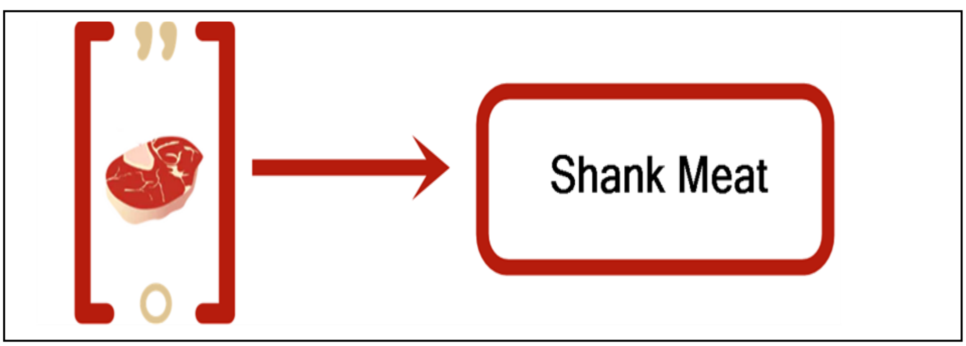

Figure 2. Block Diagram of the Application

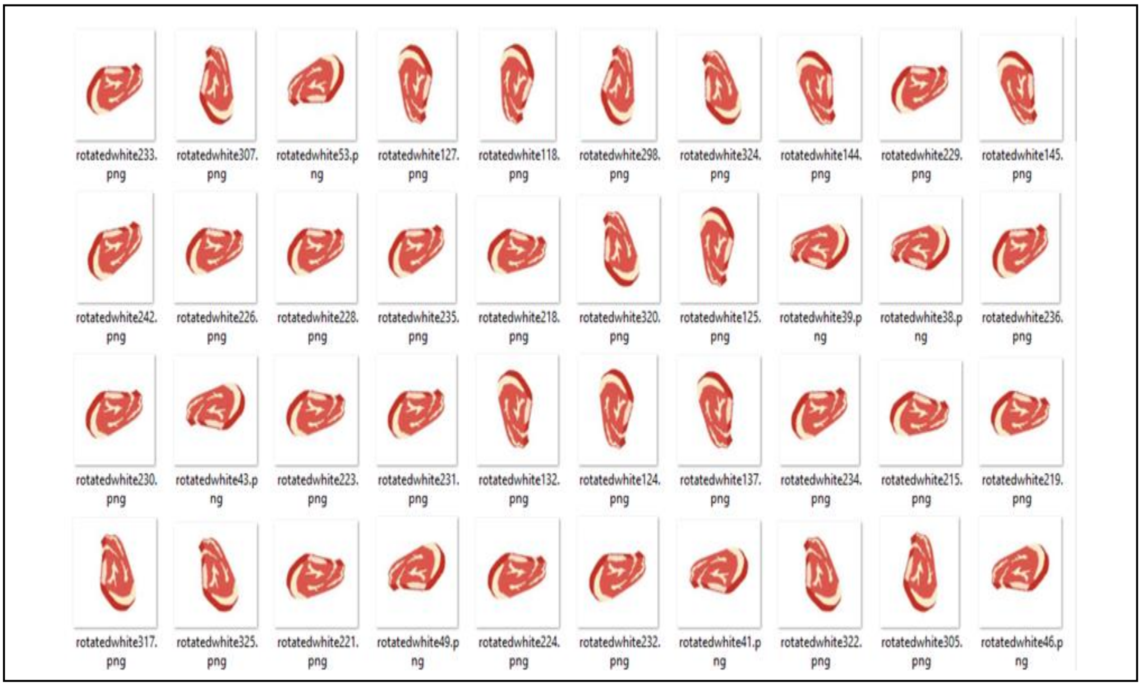

Figure 3. Rotation of the Meat

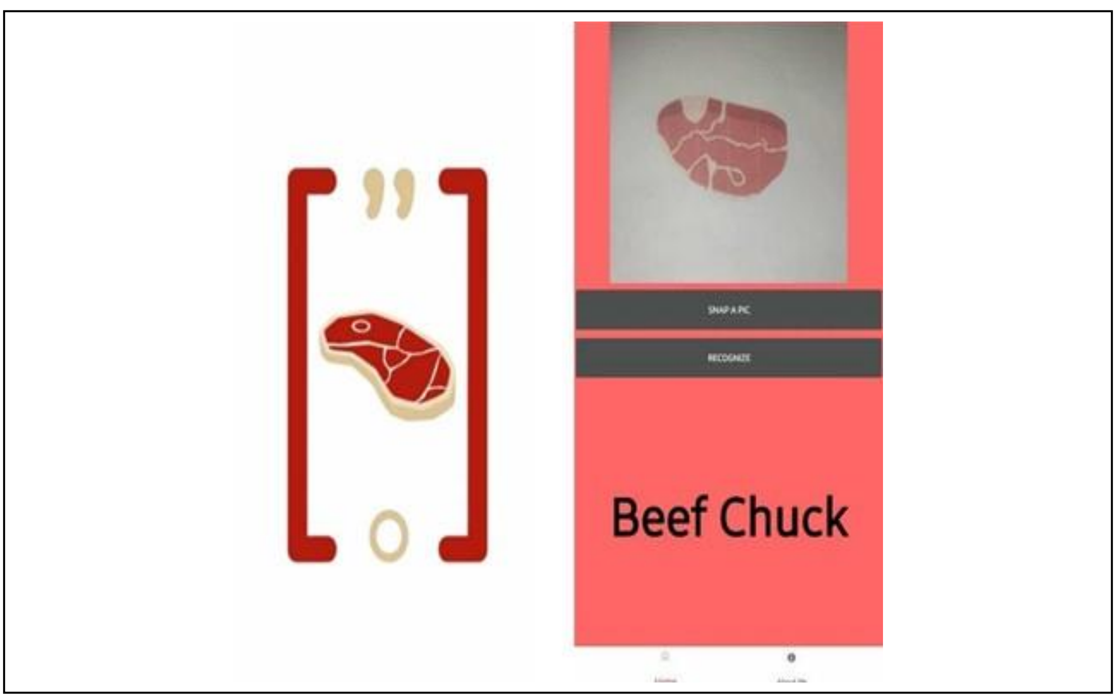

Figure 4. HiwAppUI

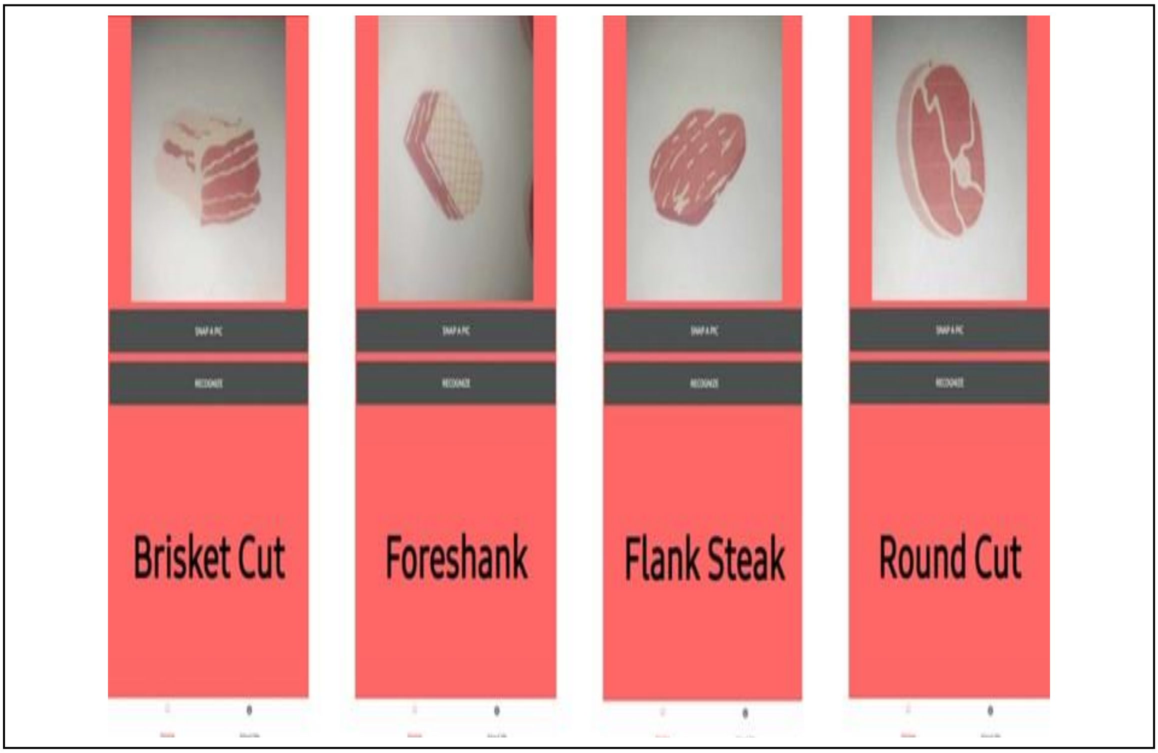

Figure 5. Testing of Meat Cuts Recognition

	Rib Eye Steak	Rib Steak	T-Bone Steak	Tri-tip Roast	Rump Cap	Round Cut	Shank Meat	Flank Steak	Short Plate Primal	Foreshank	Brisket Cut	Beef Chuck
Rib Eye Steak	2	0	0	0	4	0	0	4	0	0	0	0
Rib Steak	0	10	0	0	0	0	0	0	0	0	0	0
T-Bone Steak	0	0	10	0	0	0	0	0	0	0	0	0
Tri-tip Roast	0	0	0	10	0	0	0	0	0	0	0	0
Rump Cap	0	0	0	0	6	0	0	0	0	0	0	0
Round Cut	2	0	0	0	0	8	0	0	0	0	0	0
Shank Meat	0	0	0	0	0	0	10	0	0	0	0	0
Flank Steak	0	0	0	0	0	0	0	10	0	0	0	0
Short Plate Primal	0	0	0	0	0	0	0	0	4	0	0	0
Foreshank	0	0	7	0	0	0	0	0	0	3	0	0
Brisket Cut	0	0	0	0	0	0	0	0	0	0	10	0
Beef Chuck	0	0	0	0	0	0	0	0	0	0	0	10

Figure 6. 12x12 Matrix for HiwApp Test Data