Final Report

AUSTRALIAN MEAT PROCESSOR CORPORATION

Primal to Steak

Proof-of-Concept Project for Meat Traceability

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1.0 Executive Summary

A grand challenge in establishing meat traceability lies in the physical separation between meat products and their labels. This is especially the case at the downstream of the meat supply chain when products reaching end consumers. To address this challenge, this project validates the concept of using meat products themselves as unique 'fingerprints' to establish supply chain traceability.

The approach takes photos of meat products at different times and employs an algorithm to compare these photos to see whether they are from the same piece of meat or not. If the concept proves to be working, consumers can use their mobile phones (or similar devices) to validate the authenticity of the products they purchase. The project team designed an approach which transforms a meat photo into a measurable array. Arrays from different photos are then compared to reach the traceability conclusion.

As a proof-of-concept project, the approach was applied to beef products in two formats: with package and without package. With package meaning the beef's picture is taken when it is still inside its packaging, with labels and prices included. Without package meaning the picture is taken when beef is out of the packaging by itself. This guarantees that the product is entirely shown and makes the meat feature extraction much easier. This project mainly focused on beef products without packages as this is the key to establish traceability based on the products themselves.

The identification of beef without package is extremely similar to the leaf cultivar identification problem and warrants a similar approach. We first remove the background of the image and convert it to grayscale, then use LRsCoM technique to extract the feature out of the beef image. This method takes translation, rotation, and size into consideration, so it does not matter if the beef is presented in a different manner. Distances could be calculated between any pair of photos and these values are used to judge whether two photos are from the same piece of beef or not.

For beef without packaging, the project team managed to reach an accuracy of 99.15%, 89.83% precision and 74.65% recall. Here we see clear evidence that beef products are able to be traced back within the first week, i.e., before the meats go off. For beef with packaging, the accuracy was 92.56%, precision 100%, and recall 18.18%. Although it has a high accuracy, this cannot be taken as face value with such a low recall rate. The low recall rate indicates it is impossible to consistently and correctly identify beef with packaging using the proposed algorithm, albeit it works well for beef without packaging.

Overall, the project demonstrates meat traceability can be achieved by just relying on the products themselves. Recommendations are proposed to further the research on this front, including for beef with packaging, developing advanced techniques with higher performance and robustness, deploying a mobile App for further testing and eventually promoting Australian beef, as well as improving algorithm efficiency and robustness through large scale testing or implementation.

2.0 Introduction

A grand challenge in establishing meat traceability lies in the physical separation between meat products and their labels. This is especially the case at the downstream of the meat supply chain when products reaching end consumers. While tamper-proof packages could be used, they do not always achieve what they are designed for and require additional costs. In 2018, Meat and Livestock Australia reported that only 50% of the Australian branded beef in the Chinese market was from Australia. Thus, the viability of the meat export trade could be significantly impacted if such risk factors are not properly managed, as can be seen from the decline of Brazilian beef exports in 2017 following several scandals.

To address this challenge, this project validates the concept of using meat products themselves as unique ‘fingerprints’ to establish supply chain traceability. Figure 1 illustrates the concept. Meat images are taken at meat processing facilities and are uploaded to a server, which is controlled by meat processors or trustworthy third parties. The products are then handled through their corresponding supply chains and reach end consumers. Consumers can use their mobile phones (or similar devices) to take photos of the meat products they purchase and query their authenticity by uploading the photos to the authentication server. The authentication server compares the uploaded product photos from both the meat processors and the consumers and sends back to the consumers the authentication outcomes.

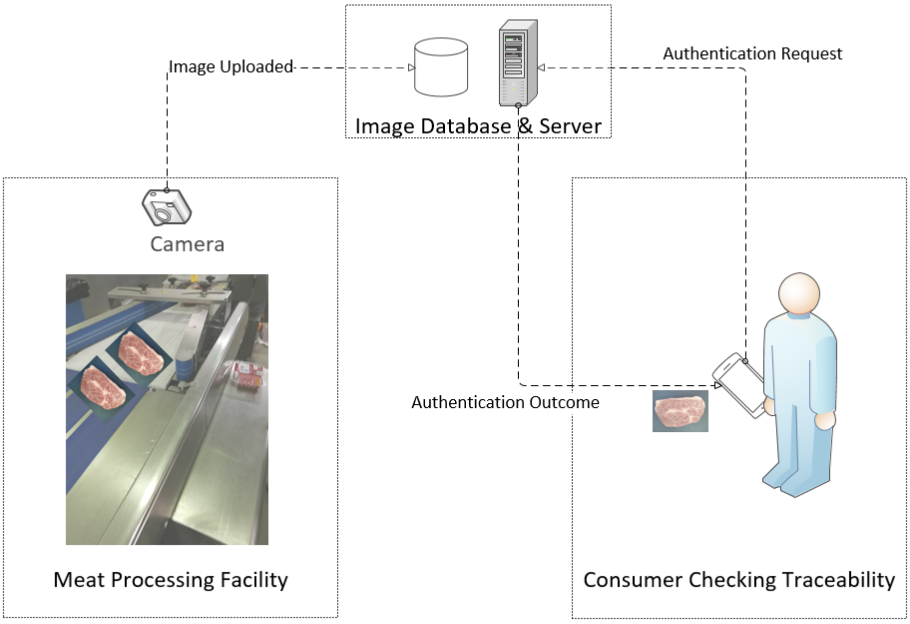

Figure 1: The supply chain traceability concept.

A similar everyday scenario of this concept is the automatic passport checking in airports. Meat traceability aims to use machine vision to identify if two meat images represent the same piece of meat. To achieve this, we will need two photos of the meat. First one is called the “passport photo”, which is the original meat. The second one is called the “passenger photo”, which will be compared to the passport photo. This is like the way that a passenger is being identified to their passport at an airport. If the two photos are similar enough, they will be classified as the same piece of meat.

Obviously, key to the success of this concept would be the ability of the authentication server to correctly identify the ‘right’ photos (i.e., photos that are taken from the same piece of meat) and not to be confused by the ‘wrong’ photos. One note to be taken here is that meat photos could be taken at different times which might introduce distortions and consequently challenge the meat authentication process. This was the focus of this proof-of-concept project.

3.0 Project Objectives

The objective of this proof-of-concept project is to uniquely identify a piece of meat product based on images taken at different times after the product is ‘released’ to the market. The project took a small batch of packaged and unpackaged beef and conducted the identification process based on product traceability validation concept proposed in Figure 1.

4.0 Methodology

4.1 Product data

In this project, both packaged and unpackaged meats were tested. Overall, 40 pieces of unpackaged (by removing packaging materials) beef products and 11 packs of packaged beef products were used. The beef products used consisted of oyster blade steaks, scotch fillet steaks, eye fillet steaks, porterhouse steaks, rump steak medallions, and T-bones. All the meats were stored in a fridge at around 4°C, over the image collecting process. Each piece of meat was taken a photo on the first day of purchase and the photo was used as the benchmark photo (‘passport photo’). In the subsequent days, daily photos were taken for each piece of meat (or pack) until the meat went off or reached the expiry date. These daily photos were used as the testing photos (‘passenger photos’). All photos were taken using a mobile phone and black matte background, under normal lighting conditions. The photos were labelled and then double checked to ensure all beef photos were labelled correctly and the same beef can be identified by human eyes.

4.2 The meat identification algorithm

To correctly recognise whether two photos are coming from the same piece of meat, the overall process in Figure 2 was applied. The identification framework first removes the background so that contour of the meat could be easily constructed as it is essential to have such information for meat identification. The LRsCoM method, proposed in Wang, Gao, Yuan and Xiong (2020), was then applied to extract the features of the contour so that difference with other contours (measured as ‘distance’) could be calculated. A threshold was then applied to the distance to indicate whether two photos are from the same piece of meat or not. The detailed explanation to this identification framework is provided in the rest of Section 4.0.

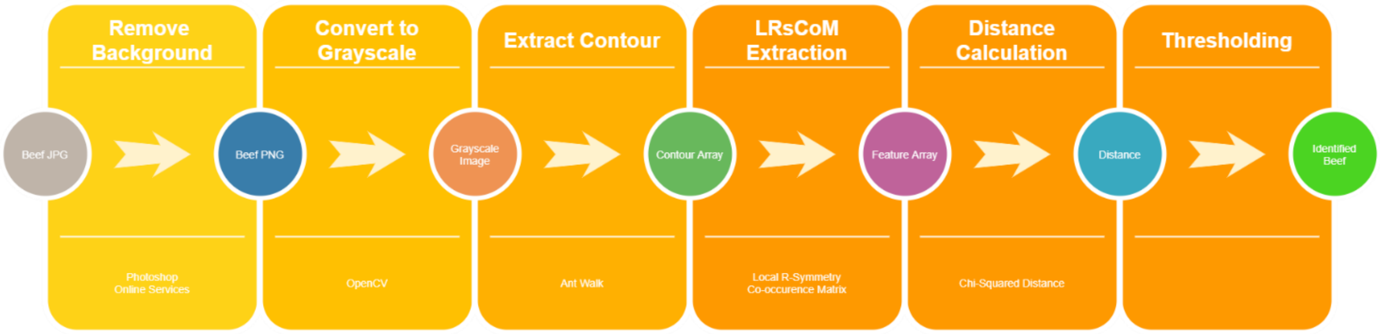

Figure 2: The overall process of identifying meat products.

4.2.1 Background removal

To ensure the beef’s contour is correctly extracted, we first remove the background of the beef and then take the outer pixels’ position as the contour array. There are many ways to do this. For example, the Otsu’s method (Otsu, 1979), named after Nobuyuki Otsu, is an automatic image thresholding method. Given a grayscale image, it will return a single value that will separate between foreground and background. This method works well when the subject is distinctly different than the background, and when there are little to no shadows.

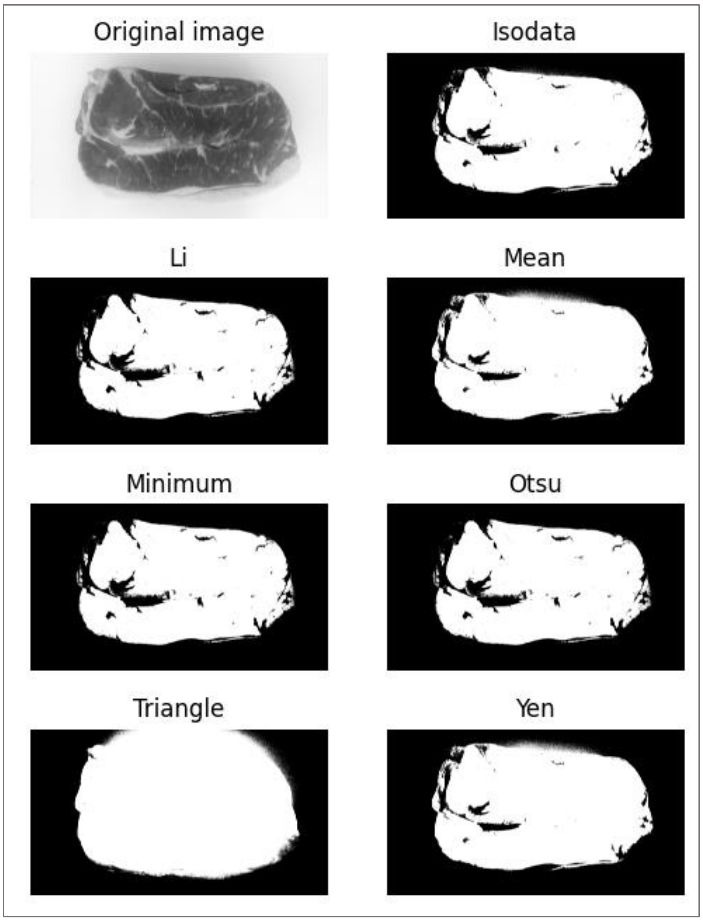

Figure 3: Contour segmentation results from Otsu's method and a number of others from the literture.

Figure 3 shows Otsu's method alongside with a number of other thresholding methods in action. None of these methods can perfectly segment the beef. Since the beef has white fat on its outer edges, sometimes the shadow (as photos were taken with normal lighting conditions) will be more intense than the white fat so it is impossible for the thresholding method to return a perfect threshold that can separate beef from background. The methods of Otsu, Li, Isodata, etc. mistake the white fat as background, resulting in an imperfect contour. The Triangle method over thresholds and produces a giant blob that does not describe the exact shape of the contour.

To address the challenges shown in Figure 3, local thresholding could be applied. This approach divides the image into small chunks and applies individual thresholding for each chunk, rather than having a single value dictating the threshold. This works especially well when there is a lighting difference or when there are shadows in certain areas, as can be seen in Figure 4. However, it is rather difficult to fine tune a set of parameters to work for all images. One set of parameters might work for one set of images but fail for another. Therefore, the results are volatile and unreliable.

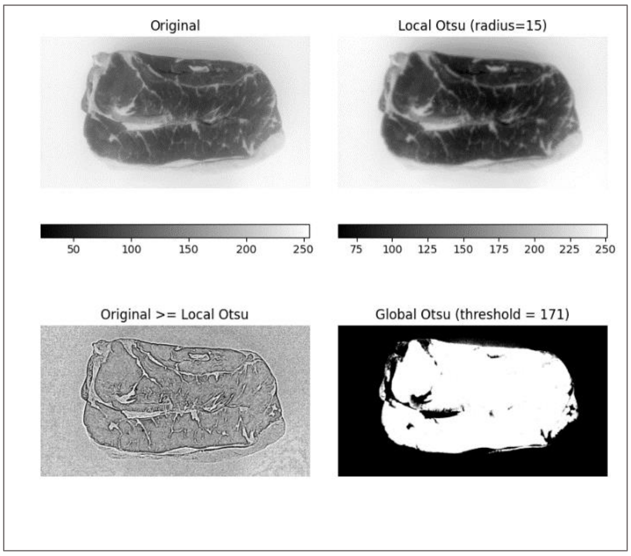

Figure 4: Result of applying local thresholding to a beef image

There are also online background removal services, most of which train machine learning models to remove the background. The project team tried the following online services which all provide excellent background removal:

- https://www.remove.bg/ (Paid with free preview)
- https://removal.ai/ (Paid with free preview)
- https://photoscissors.com/ (Free, does not support bulk removing)
- https://pixlr.com/remove-background/ (Free, does not support bulk removing)

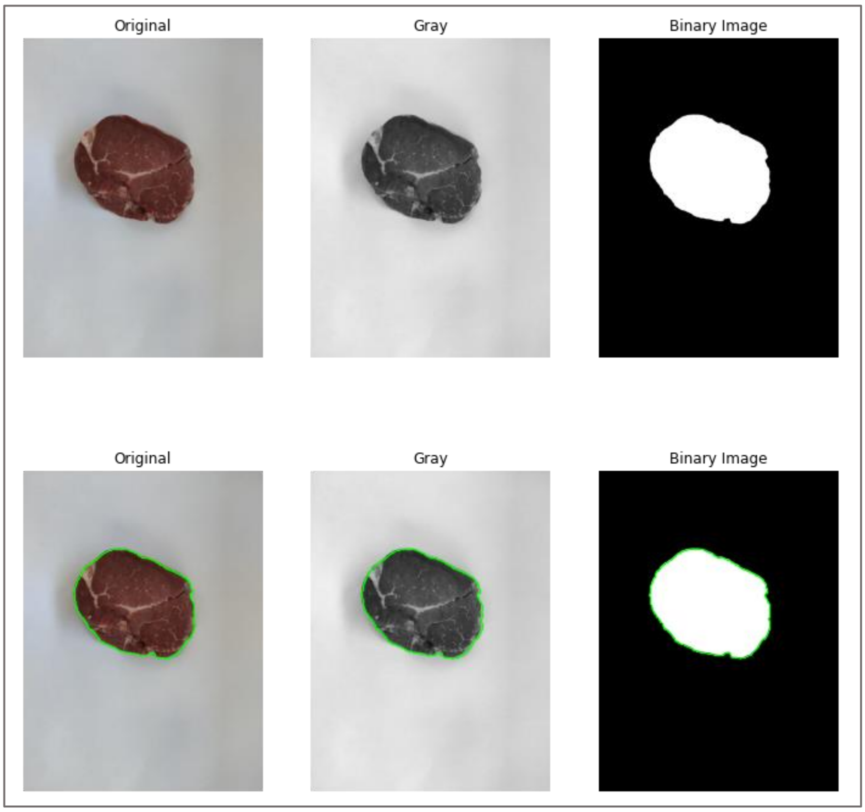

Figure 5: Contour segmentation using Photoshop (top row showing the raw result, bottom row showing green contours).

Photoshop can also be a candidate for background removal. A bulk removal can be done simply by running a custom script. It segments the beef perfectly when it is outside of the package, as illustrated in Figure 5. However, when the beef is inside of the package, this task is almost impossible. As there are no consistent pattern (e.g., pack background) and labels could block parts of the beef.

4.2.2 Converting to grayscale

This step can be done with any image processing tool, such as OpenCV or PIL (Python). The LRsCoM algorithm used can only take single channel images, so it is impossible to process the original coloured image. Therefore, it is necessary to convert the photos to grayscale. It should be mentioned that the LRsCoM method can also work on individual RGB (Red, Green, Blue) channels if desired.

4.2.3 Extracting contour

The contour array of a beef image was constructed by first converting the picture into a binary image (where the background pixels are ‘0’ and foreground pixels are ‘1’), followed by tracing the outer layer of ‘1’s. Specifically, the ant walk method was applied:

1. Find all pixels that are ‘1’ with a ‘0’ on top of them.
2. For each pixel trace clockwise to find the next ‘1’ pixel.
3. Keep tracing until a dead end or the original pixel has been reached.
4. For all pixel traces, find the biggest one and return it.
5. Since the beef should be the biggest object in the image, the biggest contour array should be the beef’s contour array.

4.2.4 LRsCoM extraction

The LRsCoM method was originally designed and developed by our team to identify leaf cultivars (Wang, Gao, Yuan and Xiong, 2020). The feature is extracted by sweeping through the leaf. In this case, we treat the beef as a special type of leaf.

A brief explanation of how the LRsCoM algorithm works can be described as: By randomly sampling points around the contours and creating matrices that represent the area each sample point has swept, a single 1D array can be obtained by measuring their entropy, dissimilarity, autocorrelation and concatenating them. This final array is the extracted feature of the input beef image. Once obtained, the final array can be compared with other extracted features.

4.2.5 Distance calculation

We measure the similarity or dissimilarity of two beef feature arrays by calculating their ‘distance’. The distance can be calculated using the χ^2 distance calculation (Wikipedia Chi-Squared, n.d.):

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

Where *O* is the ‘passport’ beef’s feature array, *E* is the ‘passenger’ beef’s feature array, and *n* is the size of the arrays. Substituting the arrays in the algorithm will result in a single distance number, which can be used for thresholding.

4.2.6 Thresholding

With a distance calculated between two given images, we can now decide a single threshold to determine if they are from the same beef or different beef. For example, if an arbitrary threshold was decided to be 100, now any two beef images with a distance below 100 would be identified to be the same beef; any distance above 100 would be identified as different beef. To avoid arbitrary deciding a threshold value, a statistical graph was produced to determine the best threshold, which would grant the highest accuracy.

The threshold was determined to be the value that best separates two types of distances: intraclass and interclass distances. The intraclass distance is the distance between two photos from the same beef. The interclass is the distance between two photos from two different pieces of beef. Based on this idea, we applied 1-D clustering for both intraclass and interclass distances and plotted their probability histograms on the same graph. A threshold was then systematically chosen to best separate the two histograms (as represented by the purple dotted line shown in Figure 6). We can see from the figure that the accuracy (on the right panel) reaches the highest level, while maintaining the precision of the separation.

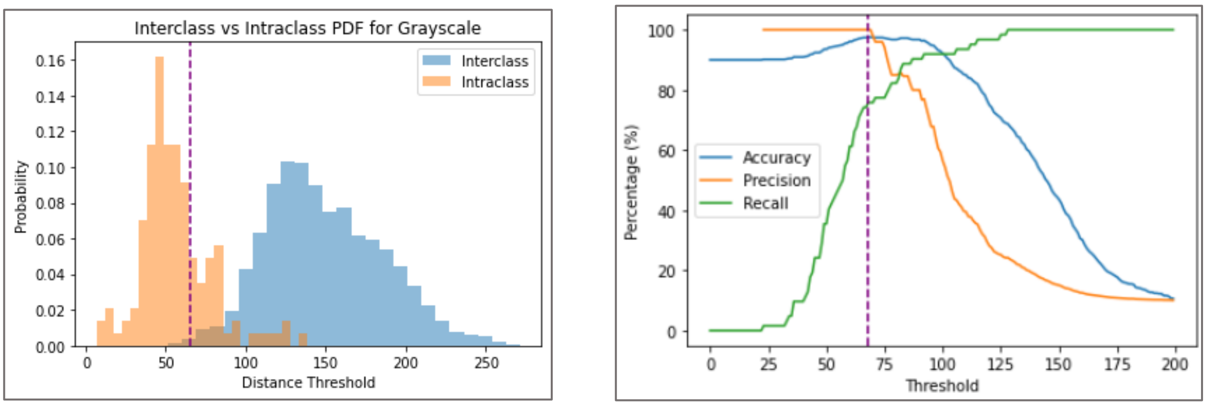

Figure 6: The threshold of 68 (the dotted line) was chosen here as it gives the best separation.

4.3 Performance measurement

As described earlier, photos were taken for meat products and stored in two categories: one by meat processors (‘passport’ photo) and the other by consumers (‘passenger’ photo). Images were randomly chosen from both categories and matched with each other. The matching results will be one of the following:

- True Positive (TP): when a ‘passenger’ beef has been identified correctly to its ‘passport’ beef.
- True Negative (TN): when a different beef has been correctly rejected.
- False Positive (FP): when a different beef has been falsely identified as a same beef.
- False Negative (FN): when a ‘passenger’ beef has been misidentified to not be the same as its ‘passport’ beef.

Based on the four types of results listed above, the performance of the proposed identification algorithm is measured using identification accuracy, precision and recall. Accuracy is measured as the sum of accurately identifying true positives and true negatives against all the number of identification attempts. Precision is measured as the number of true positives against the sum of true positives and false positives. Recall is the number of true positives against the sum of true positives and false negatives. Figure 7 graphically demonstrates how these performance measurement indicators are calculated.

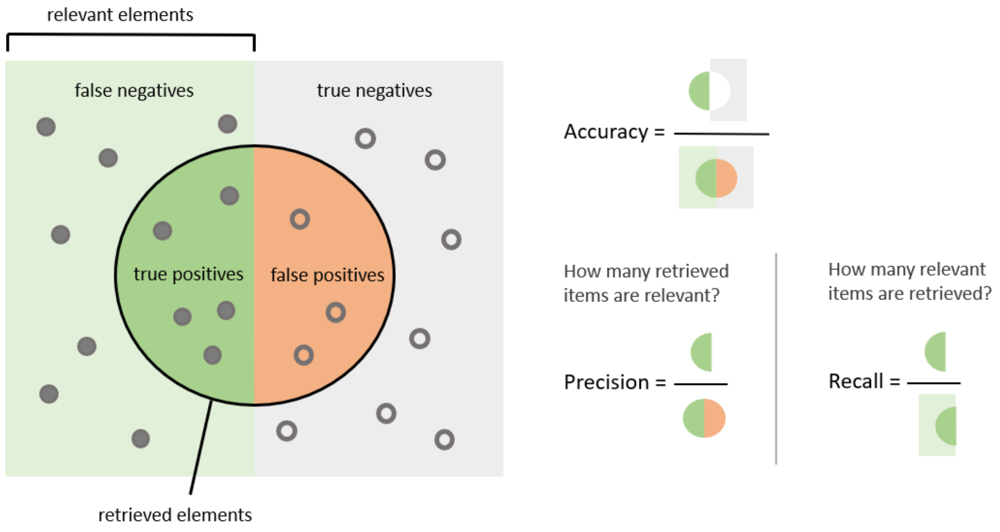

Figure 7: Graph explanation of accuracy, precision, and recall (adapted from Wikipedia Precision and Recall, n.d.).

5.0 Project Outcomes

5.1 Beef without packaging

There were 40 pieces of beef used for identification. The results showed an accuracy of 99.15%, 89.83% precision, and 74.65% recall. The high accuracy is due to the large number of True Negative results. The number of different beef comparisons succeeds the number of same beef comparisons by two orders of magnitude, as can be observed from the comparison number table in Table 1. It should be noted that a high accuracy could be achieved with an absurd number of True Negatives when the threshold is set low. Therefore, it is also important to look at the precision and recall. Precision describes out of all the positives the threshold decides, what percentage of it is correct. With a total of 118 reported positives, 89.83% of them were identified correctly. Recall is also known as hit rate, i.e., what percentage of ‘passenger’ beef has been matched to their ‘passport’ beef. With a total match of same beef 142 instances, 74.65% of them have been correctly identified as the same.

Number of Results: 5680	Predicted Positive	Predicted Negative
Actual Positive	106 True Positives (TP)	36 False Negatives (FN)
Actual Negative	12 False Positives (FP)	5526 True Negative (TN)

Table 1: Confusion matrix of unpackaged beef classification

It is also important to note that as the age of the beef increases (i.e., the number of days since the ‘passport’ photo was taken), the harder it is for the algorithm to correctly identify the same beef. This can be observed in Figure 8 regarding the average distance to the ‘passport’ photo against days since the ‘passport’ photo was taken. We can see that the average distance to the ‘passport’ photo increases as it gets further away from day 1, i.e., when the ‘passport’ photo was taken. With the idea of threshold explained earlier, it is easy to see that the higher the distance, the higher the chance two same beef will be incorrectly identified as different beef.

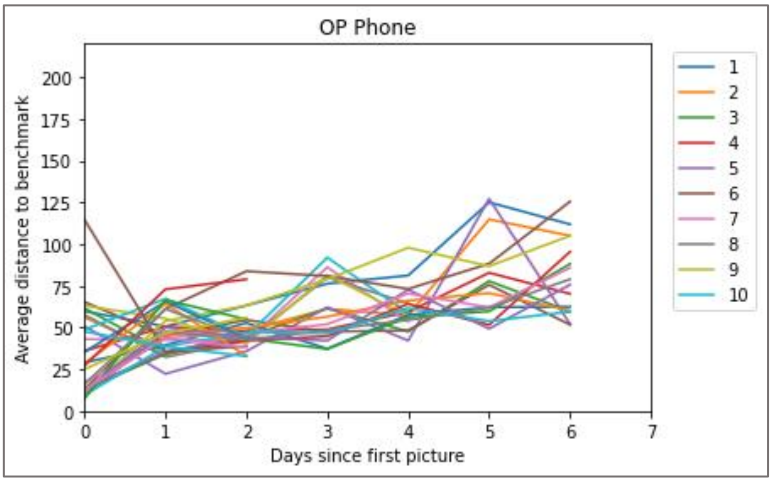

Figure 8: Average distance to 'passport' photo against days since first picture for beef without packages.

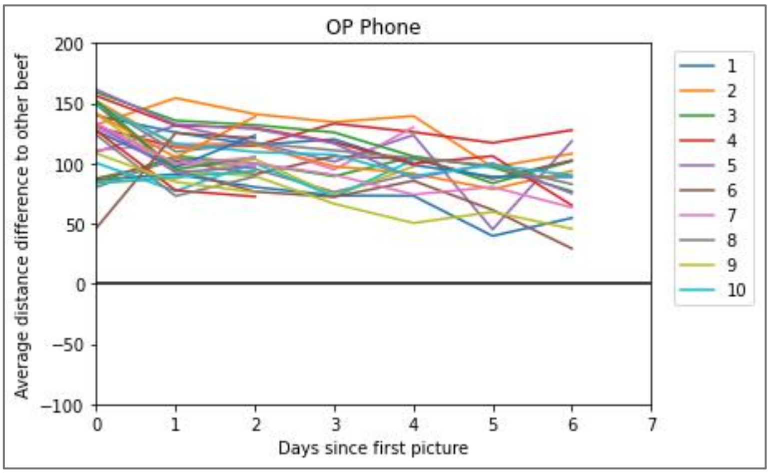

Figure 9: Average distance difference against days since first picture for beef without packages.

Figure 9 presents another aspect of the distance as days passed by, which describes the relationship between average distance difference between interclass and intraclass beef. The more it is above zero, the easier it is to separate different beef classes. If it reaches zero it means the algorithm has as good of a guess as 50/50. If it reaches below zero then it is worse than a guess. As the graph shows, the moving average slowly approaches zero as days goes on.

In conclusion, beef photos that are taken further away from the purchase date are harder to distinguish and identify. This is rather expected as unpackaged meat products deteriorated quickly, even when they were kept at around 4°C in the fridge.

Figures Figure 10 and Figure 11 show some example pictures of 'passport' beef distance to 'passenger' beef. We can see that the two pieces of beef in Figure 10 were correctly identified, while the one in Figure 11 was not.

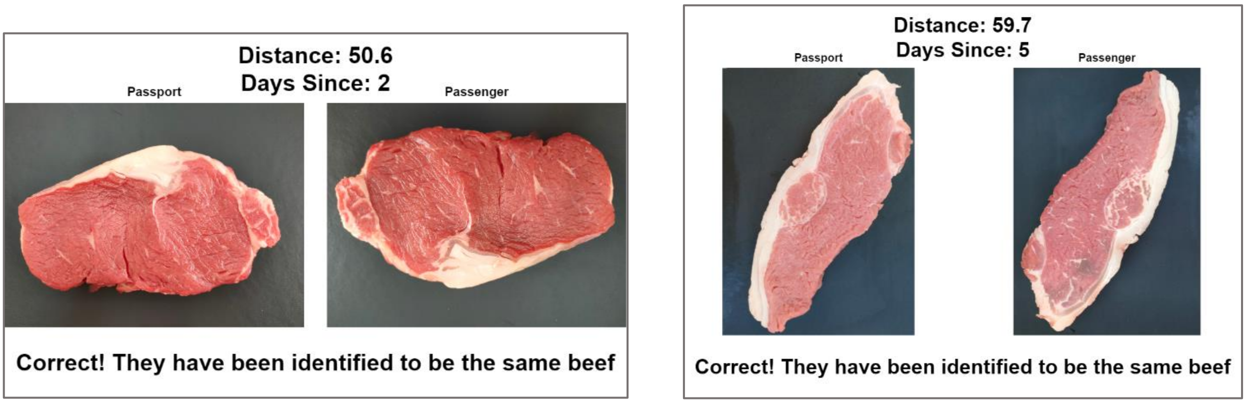

Figure 10: Correctly identified beef products without packages.

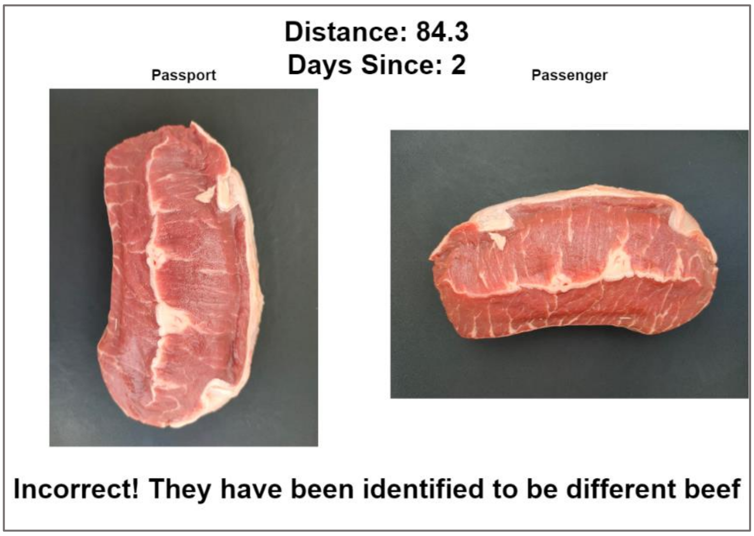

Figure 11: Incorrectly identified beef product without package.

5.2 Beef with packaging

For packaged beef, there were 11 packs in total. We apply the same approach to the unpackaged beef and reached an accuracy of 92.56%, 100.0% precision, and 18.18% recall. It should be noted that the high accuracy does not mean too much when compared to the low 18.18% recall rate. The algorithm set a rather low threshold, therefore was inaccurate even when comparing the same beef to itself. This is evidenced by the fact that out of the 33 positive comparisons, only 6 of them were identified correctly. In this sense, this is not an accurate meat identification approach.

Number of Results: 363	Predicted Positive	Predicted Negative
Actual Positive	6 True Positives (TP)	27 False Negatives (FN)
Actual Negative	0 False Positives (FP)	330 True Negative (TN)

Table 2: Confusion matrix of packaged beef classification

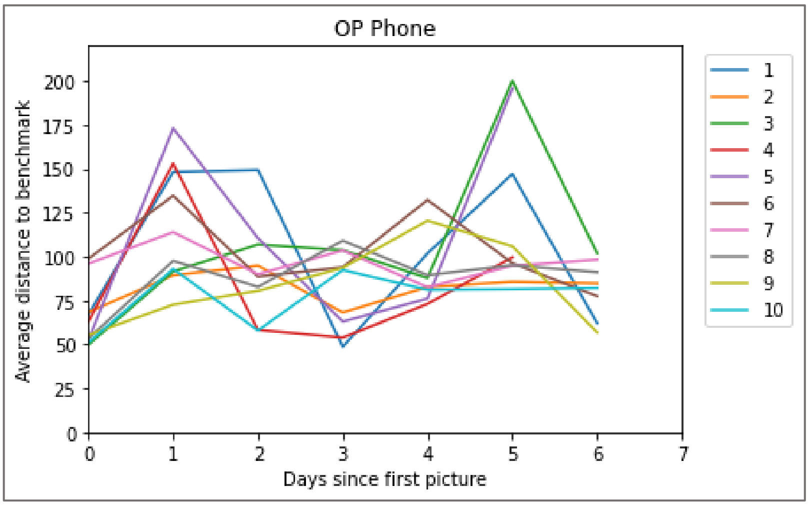

Figure 12: Average distance to 'passport' photo against days since first picture for beef with packages.

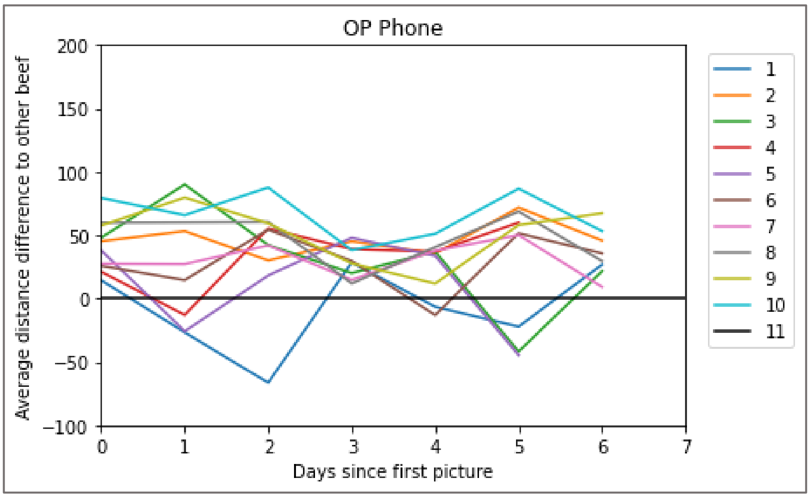

Figure 13: Average distance difference against days since first picture for beef with packages.

Figures Figure 12 and Figure 13, which are the counterparts of Figures Figure 8 and Figure 9 for packaged beef, cannot demonstrate a clear linear relationship between the distance measured between beef and the days since the first picture was taken. Due to its random nature, it makes harder to correctly identify beef products. From the existing results, it is hard to conclude that the algorithm can correctly analyse the distance when the beef is wrapped by the cover. One possible explanation is that the wrapping materials introduce randomness. For example, the label is not fixed tightly on the package, therefore is free to move when pictures are taken. Another explanation is the reflection associated with the packaging materials. These two factors could be observed in Figure 14, which presents two cases where products were incorrectly identified.

Figure 14: Incorrectly identified beef product with packages.

6.0 Discussion

The results obtained in this proof-of-concept project indicate that beef without packages can be correctly identified at least within a week, with the accuracy going down daily since the first picture is taken. The accuracy decreases over days due to beef products start to mould, decompose or swell, which could drastically change the shape of the contour. Since the LRsCoM algorithm adopted in this project is sensitive to the contour shapes, it is expected for the accuracy to have an inverse relationship with days since first picture taken.

The LRsCoM algorithm was originally designed to identify leaf cultivar by scanning the texture of leaves. In this project, the same idea was applied to beef, where a beef was taken as a very large and unique leaf and each beef is a cultivar type of their own. This should prove the flexibility of LRsCoM algorithm and its ability to compare any object with unique texture.

The reliability of the results is impacted by three major factors. The first factor is whether the beef is on a clearly separable background. Without the ability to extract the pure beef segment from the image, the feature extraction cannot produce reliable information. The second factor is whether the beef is cut off or covered by foreign objects. As demonstrated by with packaging results, any labelling covering the beef will generate almost random output. That said, the beef part which can be seen from outside the package should still be useful. The project team did not explore this option due to time and scope constraints. Lastly, how many days since the first picture was taken. Intuitively, the less the beef has aged, the easier it is to be identified.

Overall, the project has achieved its objective as a proof-of-concept project. The results demonstrate that it is possible to use images of meat products for traceability purposes. This significantly simplifies the traceability requirement along the whole meat supply chains, and reduces the possibility of meat counterfeiting.

7.0 Conclusions / Recommendations

In conclusion, this project has demonstrated that beef products without packages are able to be traceable, with the accuracy of identification going down slowly corresponding to the number of days after the first picture is taken. However, the meats remain traceable until they go off. While packaged beef cannot be traced using the same approach and therefore require further research.

Proving such a traceability concept could be a game changer for meat supply chain traceability. Traditionally, meat traceability has always relied on the integrity of supply chains. Using products themselves as the means for traceability can greatly improve the digitisation of meat supply chains and provide greater assurance of product quality to consumers, without relying on external parties such as logistics companies.

The concept proposed in this project will be the core technology to establish meat traceability. Based on the findings from this proof-of-concept project, the following recommendations are made:

- Design specialised beef matching method to further improve accuracy, robustness, and speed for industrial adoption. While the approach applied in this project proves the concept, it does not exploit the features of beef products which could compromise the accuracy, precision and recall of the traceability algorithm.
- Similarly, other types of meat other than beef could also be traced and worth further exploration. As demonstrated in this research, the idea proposed should be equally applicable to other types of meat as long as there are shapes and textures to be extracted.
- Further research is needed to establish the possibility of identifying beef with packages. Research on more effective background removal algorithm for packaged meat products is therefore required. Alternative solutions could also be tried. For example, an easy implementation might be redesigning the package in simple patterns and not covering any of the beef. Or perhaps marking the package with a simple shape in the corner. Package materials which reduce light reflection would also be helpful. These methods will help tackle the challenges encountered for products with packaging and make them traceable.
- A user-friendly mobile App to be developed. This would allow further testing for different types of mobile devices to be used under different lighting conditions.
- Expand the research project to investigate the viability of the proposed approach for large scale implementations.
- Use high resolution cameras to capture the 'passport' meat photos. High quality 'passport' photos will enable the features extracted to be richer, which would be helpful when comparing with 'passenger' photos as consumers might use different types of mobile devices which could have inferior image quality.

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