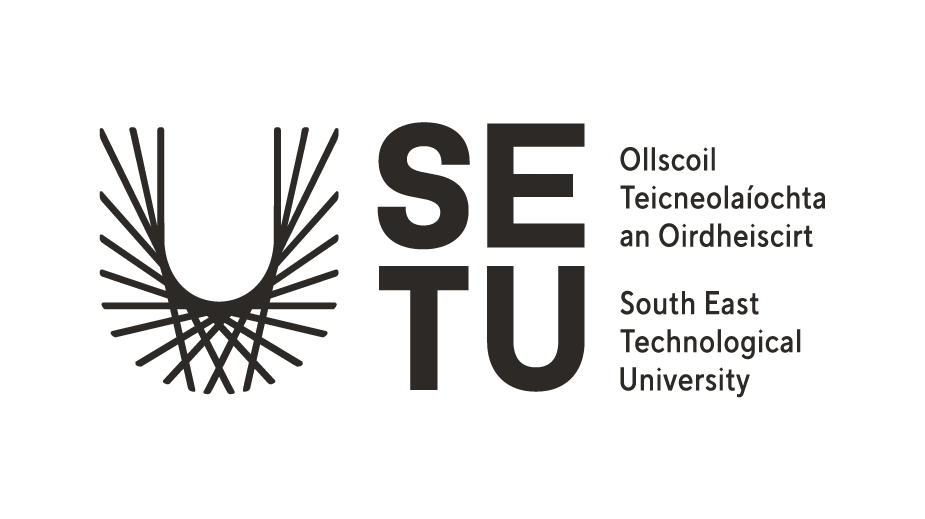
**Efficiency of Image Recognizing API’s on Food and Nutrients on the Quality of Health Tracking Food**

by

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Dissertation Proposal

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# Introduction

Developed countries have 72% of adults use smart phones and among them 52% search for things related to Health. There are more than 165,000 mobile applications related to Health available in different App Stores, including paid and free versions (Allegra, Dario 2020). Health tracking around the world is becoming more popular, with people using a variety of digital tools to monitor their health(Nishida, Uauy, Kumanyika, & Shetty [2004](https://pmc.ncbi.nlm.nih.gov/articles/PMC7859960/#ref80)). Most commonly everyone uses Mobile Apps to track their health which includes calorie intake, activities like walking, running, swimming and cycling. Even though mobile apps advanced their tracking mechanism on activities like walking, running, swimming and cycling, calorie intake is mostly dependent on user entries or supervision. The nutritional calories are measured and labeled in US foods since only 20th century (Putnam, J., Allshouse, J., & Kantor, L. S. 2002). Even though calories and nutrition became relevant most recently, awareness and tracking have already spread all over the world. Most health tracking applications provide a method to track calories and nutrition intake. Understanding food and ingredients along with their nutritional value is important not only to just monitor calories but also to understand different nutrition that comes along with it. As each nutrition plays a big role in every person’s day-to-day life, more importantly for people with certain diseases. Understanding food and its nutrition is so complex as different types of ingredients can influence the nutrition values (Dewettinck, Koen 2008).

There are quite a few research that’s been going on to automate this process. The major research has been towards identifying food, ingredients and their quantities through Image recognition API’s (Allegra, Dario 2020). The technological improvement in understanding physical activity has improved tremendously whereas understanding food and its nutrition values is not. Even the best API’s have their limitations with complex foods and regional foods. And not all mobile apps have self-learning and are affordable for every type of users (Chen, J., Zhu, B., Ngo, C. W., Chua, T. S., & Jiang, Y. G. 2020).

The field of image detection and classification has developed rapidly, and many proposals of image detection and classification methods based on machine learning have greatly improved the accuracy and efficiency of image detection and classification (F. S. Konstantakopoulos, E. I. Georga and D. I. Fotiadis, 2024). Therefore, image detection and classification technology can be better applied to many practical fields and industries. Mobile applications such as menu image recognition and classification and food health management have brought great convenience to people’s healthy life and have a wide range of application scenarios. (W. Obaid and W. Mansoor, 2024)

# The Research Problem

# Research Problem Statement

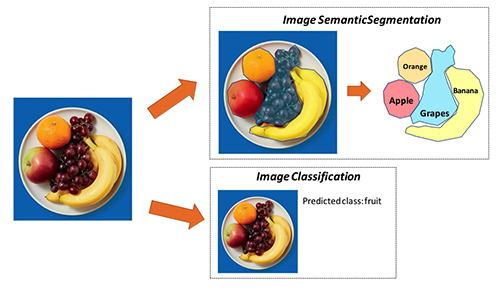
As mobile health tracking applications are advancing, people are looking for applications that can recognize food and its ingredients and track nutritional values quickly and accurately. Accurate food logs will not only help users but their physicians as well in helping patient diet (Allegra, Dario 2020). Automation due to artificial intelligence (AI) has raised manufacturing and modern industry productivity in recent decades (Kakani, Nguyen, Kumar, Kim, & Pasupuleti, 2020). Due to the tremendous processing power of graphics processing units (GPUs), neural networks can now mimic brain function. As a result, major corporations like Google, Microsoft, Amazon, Facebook, and Apple were able to start collecting data to use as the basis for their AI research (Kakani et al., 2020). The use of vision-based dietary assessment (VBDA) to extract nutritional data from images of food meals is one example of using computer vision (Wang et al., 2022).

There are many apps that can classify food, but there are only a handful of Apps that can segment different ingredients as shown below figure (Van Asbroeck, S., & Matthys, C. 2020). Even though there are only a few API’s that are available in the market that can recognize food and its ingredients, These API’s produce varying results. The Food Recognition API’s are presented in Table1. In Table 2, the author further enhanced Table 1 to add whether the listed API has Food Recognition, Segmentation, Quantity and Nutrients capabilities.

|  |  |  |
| --- | --- | --- |
| Platform | Version | Specifically developed for food |
| Google Vision API | Unknown | No |
| IBM Watson Recognition | Unknown | No; employs a food module when estimating food in general model |
| Amazon Rekognition | Unknown | No |
| LogMeal | Unknown | Yes |
| FoodAI | Unknown | Yes |
| Clarifai | 1 | No; we used the included module developed specifically for food |
| Snappy Meal | 0.0.1 | Yes |
| Lose It | 9.6.14 | Yes |
| Bitesnap | 1.5.6 | Yes |
| Foodvisor | 2.3 | Yes |
| Calorie Mama API | Unknown | Yes |

**Table1: Food Recognition API platforms identifying food images** (Van Asbroeck, S., & Matthys, C. 2020)

The accuracy of results from these Food Recognition APIs majorly depends on quality of images and type of food. There is a lack of food images taken from different cultures and parts of the world which makes it difficult for Machine learning algorithms to recognize all kinds of food. (Kaushal, S., Tammineni, D. K., Rana, P., Sharma, M., Sridhar, K., & Chen, H. H. 2024). Are the available food recognition API’s providing desired results and helpful for users?



**Figure 1: Image Classification vs Image Segmentation** (Allegra, Dario 2020)

The most critical part of an effective Food recognition API would be to identify which part of image has food, what are the ingredients, quantity of those ingredients and their respective nutritional values (Allegra, Dario 2020).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| API Platform | Specialty in Food | Food Recognition | Segmentation | Quantity | Nutrients |
| Google Vision API | No | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill |
| IBM Watson | No | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill |
| Amazon Rekognition | No | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill |
| LogMeal | Yes | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill |
| Food AI | Yes | Checkmark with solid fill | Close with solid fill | Close with solid fill | Close with solid fill |
| Clarifi | No | Checkmark with solid fill | Checkmark with solid fill | Close with solid fill | Close with solid fill |
| Snappy Calorie | Yes | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill |
| Lose It | Yes | Checkmark with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill |
| Bitesnap | Yes | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill |
| Foodvisor | Yes | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill | Checkmark with solid fill |
| Calorie Mama API | Yes | Checkmark with solid fill | Close with solid fill | Close with solid fill | Checkmark with solid fill |

**Table2: Food recognition API’s and its features** (source: Author)

# AIM

The number of health tracking applications is rapidly increasing. And most of the applications are focused on tracking user activities and their nutrient intake. Among the applications that can track nutrient intake, almost all of them need some kind of input from user’s to increase accuracy (Li, X., Yin, A., Choi, H. Y., Chan, V., Allman-Farinelli, M., & Chen, J. 2024). There are only a few mobile applications that use image recognition and AI to extract the data automatically. And these apps and API’s involved are not available in the open market for more research. The critical functionality that’s missing in the open-source world is identifying the quantity of ingredients from image recognition. And integrating the same in finding their nutritional value.

# Objectives of the study

1. Identify the Food Recognition API’s that can recognize ingredients and nutritional value in a food image.
2. Analyze and classify the functionalities that are offered by the Food Recognition API’s.
3. Test selected Food Recognition API’s and collect the results.
4. Compare the accuracy and quality of the results between different Food Recognition API’s
5. Analyze and Understand Food Recognition API available in open-source community.
6. Enhance the Open-source Food Recognition API functionality using Open AI.
7. Test the Open-source Food Recognition API using food image dataset.
8. Compare the quality of Food Recognition abilities between open-source and proprietary API’s.

# Research Questions

There is much ongoing research to automatically recognize food, ingredients and their respective nutritional values accurately. But still there are a lot of open questions in their accuracy and availability (Li, X., Yin, A., Choi, H. Y., Chan, V., Allman-Farinelli, M., & Chen, J. 2024). The critical functionality that gains more advantage in proprietary model which is not available in open source is identifying quantity of ingredients in food images.

The following research questions (RQs) have been formulated for this study:

**RQ1:** How accurate Proprietary Food Recognition API’s in identifying food, quantity and nutritional value from an Image?

**RQ2:** How Open AI can enhance Open-Source Food Recognition API’s?

**RQ3:** How accurate Open-Source Food Recognition API compared to Proprietary Food Recognition API’s in identifying food, quantity and nutritional value from an Image?

|  |  |
| --- | --- |
| Research Questions | Objectives Addressed |
| RQ1 | 1, 2, 3, 4 |
| RQ2 | 5,6 |
| RQ3 | 7,8 |

**Table 3: Corelate Research Questions with Objectives**

# Conclusion

There are number of API’s available in the market, but they are expensive to build an application. And there is very limited research done in identifying quantity and nutritional value from Food Images. Any new research and development in food recognition would be really appreciated by the open-source community.

# Preliminary Literature Review

The literature related to the proposed research will be examined and reviewed in this Preliminary Literature Review section.

# Image Recognition

In any image identification, the algorithms are trained using a specific set of images which is typically called a training set. These algorithms are further evaluated using the images that are not included in the training set. The aim of image classification is to assign one predefined class to new instances of image depicting a food instance. During the training stage, the training images are processed through a variety of classifier and vector models. Once a model is trained then further input image is compared with a set of already known images (i.e., training images) and the identification is performed comparing the images through similarity measures after their representation in the feature space. (Allegra, Dario 2020)

Convolutional Neural Networks (CNN) is a popular and widely used neural network in computer vision based research. Figure 1 explains how images are being processed through CNN Model sequential convolution and pooling processes. And how images are processed as feature maps and classified through the entire connection layer. (Lubura, J., Pezo, L., Sandu, M. A., Voronova, V., Donsì, F. 2022)

A diagram of a layer

AI-generated content may be incorrect.

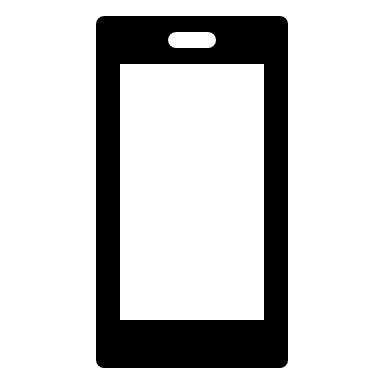
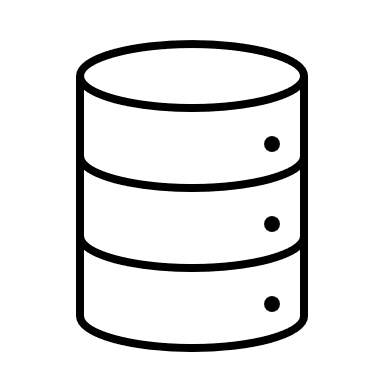
Figure 2: Image Recognition using CNN (Yanai, K., & Kawano, Y. 2015)

CNN focuses on sparse connection and weight, which helps to increase the size of the network without increasing the training data to train more complex models. To achieve the required volume layer, researchers scale the data using two linear parameters, so as to satisfy the dispersion of 1 and the average value of 0, and then input it into the lower layer through the activation function. (Nath, S.; Naskar, R. 2021)

# Food Recognition

Food is defined by the ingredients it is made of. In some foods, multiple foods combined to form a recipe. Food items are easier to identify when the ingredients are grouped in large quantities. When a food image has multiple food items, each food item may belong to different categories. Food items are differentiated and identified through their shape and color. Images processed for food recognition can be captured through phones. And different phones can produce images with different resolutions. Before processing food recognition models, these images must be standardized for better results (Zhang, W., Yu, Q., Siddiquie, B., Divakaran, A., & Sawhney, H. 2015).

Food Recognition

Food Log

Food database

Segmentation

Identify Ingredients

**Figure 2: Basic Architecture of Food Image Recognition**

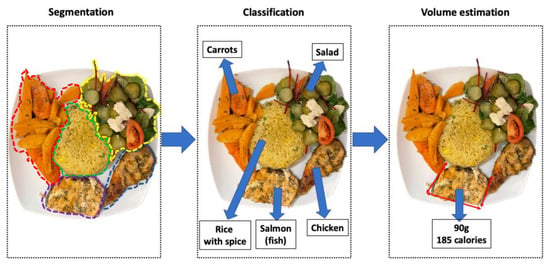
In initial research around 2010s, mobile-based classifiers in food recognition utilized support vector machine (SVM), K-nearest neighbor (KNN) and multi-kernel learning. These algorithms have been preferred due to their higher performance when compared to other classification approaches. Nadeem, M., Shen, H., Choy, L., & Barakat, J. M. H. (2023) states that Deep Learning is getting popular in food recognition research as it provides the additional edge to learn and differentiate food and its ingredients. CNN becoming one of the commonly used deep learning techniques in image/food recognition. Along with CNN, Inception V3 and Ensemble are popular as well.

Food recognition is a challenging task considering the number of recipes, cultures and ingredients. It requires a wide variety of dataset to accomplish desired accuracy. Food recognition can be a tedious task that requires a large, diverse dataset to achieve good accuracy in recognizing different types of food. Mezgec and Seljak proposed “NutriNet” that offer 225,953 images representing 520 categories of food and drinks, finetuned for deep learning. The models which used NutriNet were able to reach accuracy of 55% on real images taken with a mobile phone. Researchers were able to achieve this accuracy with just classification of food. Amugongo, L. M., Kriebitz, A., Boch, A., & Lütge, C. (2023)

# Segmentation in Food Item Recognition

Food items in a food image can be identified through segmentation. The segments are regions grouped together using similar color and texture. These grouped regions provide rich information than pixels therefore region-based features shall be used when possible. A repeated process of grouping similar regions can result in identifying a single food item. This grouping process can be done through (Zhang, W., Yu, Q., Siddiquie, B., Divakaran, A., & Sawhney, H. 2015).

* 1. Color
  2. Texture
  3. Size



In food analysis, once food recognition is accomplished, the next step is to estimate the volume of food on a given image. As part of volume estimation, first task is to precisely identify each type of food, as various ingredients can be part of a meal that is fried, baked, or cooked. Quality of a images plays key role in achieving desired accuracy of volume estimation in each image. Algorithms should be able to enhance the images and utilize a large dataset with variety of images to learn to achieve accuracy. Nadeem, M., Shen, H., Choy, L., & Barakat, J. M. H. (2023)

In literature, several techniques are discussed for volume estimation, such as

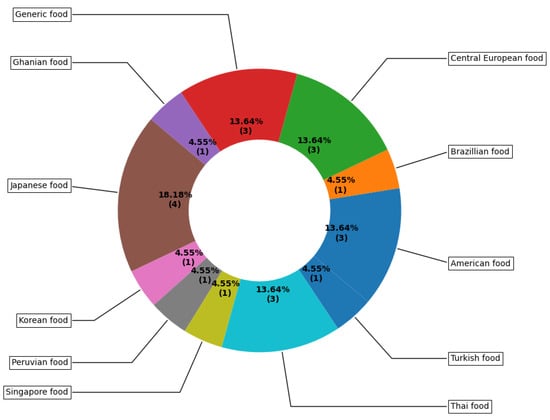
1. An approach based on pixel counting
2. Three-dimensional (3D) model segmentation.

In “Snap-n-Eat” application pixel counting is used to estimate the portion size of each segment of food. Calories and Nutrient values of each segment can be identified using food database as soon as segment of food is identified. Pixel-counting approach used in small applications as the process is quick and simple to provide good estimation of portion size. However, they assumed predefined calorific and nutritional value per food category. This assumption may not be true; for example, an ounce of baked potato chips can have 14% fewer calories, 50% less fat and less saturated fat than fried potato chips. Nadeem, M., Shen, H., Choy, L., & Barakat, J. M. H. (2023)

Applications that use Vision based dietary assessment were able to achieve better accuracy in estimating food portions compared to applications that used pixel counting. Some of the challenges reported in literatures that discussed Vison based assessment are view occlusion and scale ambiguity. Vision based assessment approaches demands variety of same images in different angles and image qualities. And to solve this, large datasets are used in deep learning and increased depth sensing techniques have been used along with AI capabilities. Amugongo, L. M., Kriebitz, A., Boch, A., & Lütge, C. (2023)

Calorie Estimation

Calorie Estimation depends on segmented ingredients and its quantity. Quantity of ingredients are estimated by calculating the pixels and comparing it to a known object. Also taking the ingredients 3D dimensions into consideration for calculations. Once the estimation of ingredients dimensions is calculated, it will lead to finding volume. Using ingredient and its volume, Calorie of each ingredient can be identified. Amugongo, L. M., Kriebitz, A., Boch, A., & Lütge, C. (2023)



Food Dataset available in open-source dataset.

# Compare and Validate Metrics

Metrics collected through proprietary API’s and Open-Source models compared and validated similar to below metrics in Table 4

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **API** | **Log Meal API** | **Foodviser** | **Open-source API** | **Fusion** |
| **Pizza** | 65.3 | 76.5 | 70.4 | 81.6 |
| **Strawberry** | 65.7 | 78.4 | 78.4 | 88.2 |
| **Mixed Fruit** | 74.2 | 76.4 | 68.5 | 82 |
| **Burger** | 48.9 | 63.9 | 61.7 | 66.9 |
| **French Fries** | 81.9 | 85.3 | 86.2 | 90.5 |
| **Green Salad** | 78.2 | 86.5 | 85.7 | 93.2 |
| **Spaghetti** | 78.6 | 79.5 | 75.9 | 83 |
| **Sandwich** | 52.5 | 61 | 59.3 | 69.5 |
| **Steak** | 62.2 | 77.3 | 72.3 | 84 |
| **Chicken wings** | 50.9 | 68.9 | 72.6 | 81.1 |
| **Sushi roll** | 54.5 | 64.9 | 62.3 | 75.3 |
| **Cheerios** | 85.7 | 84.1 | 93.7 | 92.1 |
| **Egg omelet** | 41.4 | 62.6 | 58.6 | 65.7 |
| **Pancakes** | 51.3 | 56.4 | 62.8 | 70.5 |
| **Broccoli** | 57.7 | 75 | 65.4 | 80.8 |

**Table 4: Classification Accuracy Metrics**

# Working Theory

This section will focus on the discovery of the theoretical prospect of the presented literature review. This research includes a blend of Case study and quantitative approaches.

# Methodology

Case study is chosen as a research method for initial stages of research to determine which Proprietary API’s should be taken for research. Three reasons why case study research method is a viable option for information systems research: (Kogan, N., & Lee, K. J. 2014)

* 1. The research helps to learn and generate theories from practice.
  2. The case method allows to answer “how” and “why” questions.
  3. A case approach provides a path towards valuable insights that can be gained.

Case study research will be used in finding results for RQ1.

API results will be analyzed using Cross-Sectional study for Quantitative research. Quantitative research is the numerical representation and manipulation of observations for the purpose of describing and explaining the phenomena that those observations reflect. Quantitative research is a type of research that explains phenomena by collecting numerical data that are analyzed using statistics (Sukamolson, S. 2007).

A quantitative approach will be used in finding results for RQ3.

# Bias

Bias is any trend or deviation from the truth in data collection, data analysis, interpretation and publication which can cause false conclusions. Bias can occur either intentionally or unintentionally (Simundic, A. M. 2013).

All key attributes that can contribute to biased results will be deeply analyzed carefully and kept in common between variables. Transaction time to get results between Proprietary API’s and Open-source API can be significantly different as the infrastructure is different. Hence transaction time is out of scope.

# Reliability

Reliability describes the ability of a system or component to function under stated conditions for a specified period of time. According to such definition, reliability plays a key role in the functional performance of systems (Aven, T., Insua, D. R., Soyer, R., Zhu, X., & Zio, E. 2024).

The datasets of images and samples used in this research will be retrieved from reliable resources which contribute to another similar research. And results from the research will be captured accurately without any Bias.

These are the image datasets that are considered for use in research.

* 1. Vietnamese Lunch Dataset - <https://drive.google.com/drive/folders/14rJclN97hZqe6bmGkTjnvPaDBBIF4v5w?usp=sharing>
  2. Food Image Classification Dataset - <https://www.kaggle.com/datasets/gauravduttakiit/food-image-classification>
  3. UEC Food Dataset - https://mm.cs.uec.ac.jp/uecfoodpix/UECFOODPIXCOMPLETE.tar

# Sampling

Sampling refers to the process of selecting a smaller group of items (called a "sample") from a larger set to study, with the goal of being able to make inferences about the characteristics of the whole, based on the data collected from the sample (Elfil, M., & Negida, A. 2017).

There are two major categories of sampling methods.

* 1. Probability Sampling
  2. Non-Probability Sampling

For this research, Non-Probability Sampling will be used on the basis of Judgmental approach.

All the proprietary API’s listed in Table2 will be analyzed. And 2 of them will be considered for further research according to the criteria’s mentioned below.

The criteria are.

1. Cover all critical features mentioned in Table2.
2. Popularity among Food Recognition API’s
3. Adequate access for Open-source community

By labeling, remove errors and outliers

Sampling by copying same image and rotating it in different directions and process them.

Ignoring non food contents in the image

# Research Design

This research is going to be conducted through various phases. The various phases are explained below.

The results will be compared to identify if the enhancements built through open-source are better or worse than proprietary models. And does open source need more and more research.

# Project Planning and Conclusion

|  |  |
| --- | --- |
| Date | Task |
| January 2024  January 2024 - February 2024  February 2024-March 2024  April 2024  May 2024  May 2024-June 2024  July 2024  August 2024  September 2024 | Presentation of dissertation proposal.  Develop suitable Research methodology.  Develop tests for measurements.  Enhance open-source API with additional scope.  Interim report submission.  Work on Report and continue learning.  Complete draft of final dissertation for supervisor.  Conclusion.  Dissertation Submission and Dissertation Presentation and Assessment |

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