ESTIMATION OF SALAD BAR VEGETABLE PLATE WASTE IN A MIDDLE SCHOOL SETTING USING A DIGITAL IMAGE RECOGNITION MODEL

By

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ABSTRACT OF THE THESIS

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Background: The school lunch environment is a prime target for increasing a child's consumption of fresh fruits and vegetables. Schools are using smarter lunchroom strategies to facilitate healthy choices. However, there is an increasing concern about food waste, especially at school food services. Plate waste at school lunch is used to assess menu performance and meals acceptance using a variety of methodologies. The gold standard for measuring plate waste is the weighing method which is time consuming and costly. This has led researchers to search for alternatives.

Objective: The study aims to test the feasibility and validate the accuracy of a digital image recognition model as a tool to quantify aggregate vegetable waste and compare it against the gold standard "weighing method" in a middle school.

Design: The study was divided in two phases. In phase I, images and weights of the salad plate pre and post consumption were recorded. The model was trained using these data to test the feasibility of model for predicting food classes and estimating physical weights of food. In Phase II, digital images and weights of the salad plates pre and post consumption were recorded and run through the trained model. Aggregate vegetable waste was calculated as the difference between the recorded weights, and the predicted weights assessed through the model.

Results: In Phase I, the image recognition model achieved overall classification accuracy of 85.7% of predicting nine food classes. The mean rank for recorded pre weight was (1.61 g ± 0.43 g) and predicted pre weight was (1.01 g ± 0.99 g) The feasibility results suggested that there was a significant difference between the recorded and predicted weights ($p=0.009$). In Phase II, the mean rank for recorded pre weight was (1.63 g ± 0.45 g) and predicted weight was (1.73 g ± 0.22 g) and did not elicit a statistically significant difference as compared to manually recorded weight ($p = 0.341$). The mean rank for recorded post weight was (0.62 g ± 0.77 g) and weight predicted by the image recognition model was (0.63 g± 0.80 g) with no statistically significant difference between the two ($p=0.619$). The mean rank for recorded plate waste was (0.68 % ± 0.83%) and plate waste determined by the predicted weights by the image recognition model was (0.72 % ± 0.91%). The Wilcoxon signed-rank test showed no statistically significant difference ($p=0.177$) in plate waste calculated using two methods.

Conclusion: The main findings from this study were that the image recognition model was feasible and accurate for identifying food classes and quantifying vegetable plate waste in a self-serve salad bar in a middle school and did not differ significantly from the gold standard weighing method. This study supports the use

of a digital image recognition model as a valid tool to semi automate data collection and estimate food waste.

ACKNOWLEDGEMENTS

"The dream begins with a teacher who believes in you, who tugs and pushes and leads you to the next plateau, sometime poking you with a sharp stick called "truth" ~ Dan Rather "

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1. INTRODUCTION

Fruit and vegetable intakes have been associated with obesity and chronic disease prevention as well as improved overall health status among adults (Bazzano et al., 2002; Boffetta et al., 2010; Harding, 2008; Ledoux et al., 2011; Liu, 2003; Van Duyn & Pivonka, 2000) due to the high amounts of fiber and phytonutrients found in them (Pandey & Rizvi, 2009; Slavin & Lloyd, 2012). It is important for children to consume a variety of fruits and vegetables at a young age as healthy eating behaviors during childhood have been associated with healthy food choices into late adulthood (Maynard, 2006; Savoie-Roskos et al., 2017).

1.1 Gardening Intervention in School

The school lunch environment is a prime target for increasing a child's consumption of fresh fruits and vegetables and has a powerful role in shaping children's eating behaviors. (Slusser et al., 2007; Story et al., 2009). Providing fresh fruits and vegetables on salad bars during lunch is an approach schools have been encouraged to use to boost student fruit and vegetable exposure and intake. In an effort to improve lifelong healthy eating habits and to increase fruit and vegetable intake in children, numerous public health programs and policies have been implemented. (Savoie-Roskos et al., 2017). Savoie-Roskos et al. (2017) conducted a systemic review that included studies conducted in developed countries on gardening interventions that have been implemented in various school and community settings in an effort to increase children's fruit and vegetable consumption by expanding knowledge, exposure and preference for a variety of fruits and vegetables. Although the evidence is somewhat mixed, most available studies suggest a small but positive influence of gardening interventions on children's fruit and vegetable consumption (Savoie-Roskos et al., 2017).

Gardening-based programs have been implemented in school and community settings as a way to increase consumption of fruits and vegetables by children. (Berezowitz et al., 2015; Gatto et al., 2012; Heim et al., 2009; Hutchinson et al., 2015). Teaching school children how to plant, grow, harvest, and prepare fruits and vegetables may be an effective strategy for increasing fruit and vegetable intake (Robinson-O'Brien et al., 2009). Furthermore, encouraging children to regularly participate in gardening activities is consistent with the literature, which suggests that regular exposure to fruit and vegetable increases consumption of fruits and vegetable as healthy snacks among children. A study conducted in fifth to sixth grade children from May to August to study the effectiveness of a nutrition program like thrifty gardens, basic gardening, growing techniques, ABC'S of healthy eating, demonstrated that students ate fruit and vegetable as snacks after participation in nutritional programs (Koch et al., 2006; Patrick & Nicklas, 2005). Schools are using smarter lunchroom strategies to facilitate healthy choices. School salad bars are cited as a strategy to increase fruit and vegetable intake within the National School Lunch Program (NSLP). (USDA: The national school lunch program: Fact sheet .,2017).

1.2 Ecospace Program at Philip's Academy Charter School

One school-based program called Ecospaces has been designed at Phillips Academy Charter School (PACS) in Newark, NJ. It is designed to give students the tools to lead healthy lives. The goal of the program is to educate students on food, wellness, and sustainability through hands-on, interactive learning so that they will make informed decisions to benefit their well-being. PACS uses interactive tools like family style dining, teaching kitchen and central salad bar to develop healthy relationship between children and food. The garden is used as a classroom to reconnect students with the natural world and the true source of their food. Students plant seeds, water, and nurture a variety of plants in the rooftop garden that is used for consumption in lunch at the cafeteria or in the teaching kitchen. As they understand the harvest, they are able to taste the harvest at the salad bar or in the main meal (http://www.ecospacesed.org/).

1.3 Plate Waste in School

In spite of these efforts, there has been an increasing concern about food waste, especially at school food services (Baik & Lee, 2009; Engström & Carlsson-Kanyama, 2004; Getlinger et al., 1996). The National School Lunch Program (NSLP) is one of the largest federally assisted meal programs in the United States. (Nutrition Standard in the national school lunch and school breakfast programs 2012). In 2012, new federal standards were implemented as a part of the Healthy, Hunger-Free Kids Act of 2010 (HHFKA). These standards aligned the NSLP with the 2005 Dietary Guidelines for Americans (Healthy, Hunger-Free Kids Act, 2010). Under the HHFKA, the NSLP established weekly offerings of dark green and orange vegetables and legumes, portion sizes of a half-cup or greater for fruits and vegetables, and a requirement that students must take at least one fruit or vegetable as a component of an NSLP meal (Nutrition Standard in the national school lunch and school breakfast programs & nbsp.,2012).

The updated NSLP guidelines were met with support, but also criticism. Initially, there was concern that the fruit and vegetable requirements would increase plate waste among students (Byker et al., 2014). Recent studies have shown the guidelines increase student selection of fruit and vegetables without significantly increasing waste (Cohen et al., 2013; Schwartz et al., 2015). However, these studies assert that fruit and vegetable plate waste remain a major problem with up to 75% of vegetable selections and 40% of fruit selections being discarded by students.

Plate Waste is defined as the quantity of edible food served that is uneaten at the end of the meal. By measuring the amount served and subtracting plate waste, nutritionists can estimate the amount of food consumed.

Plate waste at school lunch is commonly used to assess effectiveness of menu performance, meals acceptance, dietary intake adequacy, economic impact and efficacy of nutrition educational programs (Clark & Fox, 2009; Connors & Rozell, 2004; Crepinsek et al., 2009; De Keyzer et al., 2012). Plate waste at school may also lead to an inadequate intake of nutrients. Children wasting a high percentage of the National School Lunch Program (NSLP) lunch are likely to replace these calories with higher calorie salty and sugary foods (Cohen et al.

2013; Simon et al., 2008). Also, there are significant financial and health costs associated with plate waste. (Plate waste in school nutrition programs final report to congress; 2002).

1.4 Measuring Plate Waste

Plate waste in children's school lunches has traditionally been measured using one of the following four methods: the direct weighing method (Adams, et al., 2005; Cohen et al., 2013; Jansen & Harper, 1978) and indirect methods such as visual estimation (Comstock & Symington, 1982; Connors & Rozell, 2004; Graves & Shannon, 1983) digital photography (Marlette et al., 2005; Nicklas et al., 2012; Williamson et al. 2003) and food consumption recalled by children (Comstock & Symington, 1982; Paxton, et al., 2011).

1.4.1 Direct Weighing Method

The direct weighing method is the most accurate method and is considered the gold standard method for measuring plate waste. School lunch trays are taken from the serving line and food items are weighed separately. At the end of the meal, leftovers of each food item are weighed. The final plate waste data are generally calculated in terms of the percentage of food that was not consumed: Percent waste = (Edible waste weight / weight of mean serving size of edible food) * 100. (Plate waste in school nutrition programs final report to congress, 2002). Although obtaining weights of food waste is accurate and provides detailed information of plate waste, it is disruptive for food service, costly and time consuming. It also requires a great deal of space for holding trays and to scrape food until weighing is completed. In addition, it may influence children's intake since this method takes time and delays the delivery of plates to children and is usually impractical for large sample sizes. Moreover, children could leave the school canteen without having lunch (Plate waste in school nutrition programs final report to congress,2002; M Comstock et al.,1981).

1.4.2 Visual Estimation

Visual estimation is less accurate than a direct weighing method (Comstock et al., 1981). The observers make judgments about the proportion of average serving sizes that remain on the discarded school lunch trays. Trained observers classify foods and estimate portion sizes for each food considering standard portions that have been previously weighed, leading to the indication of wasted proportion of the initial serving (e.g., 0%, 10%, 25%, 50%, 75%, 100%). The advantage of this method is it is time and space saving and may require fewer people than direct plate waste measures like the weighing method. However, the disadvantage is that ratings are not made on exact proportions and can differ among observers (Plate waste in school nutrition programs final report to congress 2002. A recent study demonstrated that on-site visual estimation is a valid and reliable method for measuring plate waste in a cafeteria setting. However, the visual estimation for mixed dishes is difficult to obtain as compared to non-mixed dishes. (Liz Martins et al., 2014). Another study demonstrated that it can only be used when the starting portion is standard, and it is not feasible for use with self-serve items. (Bean et al., 2018). Thus, digital photography has the potential to address this challenge.

1.4.3 Digital Photography Method

Digital photography is a promising method for unobtrusively and accurately measuring food intake in naturalistic settings, e.g., cafeterias. (Williamson et al. 2003; Williamson et al., 2004). Pre and post digital photographs are taken using a digital camera. Reference portions of measured quantities of the foods are also photographed. In the laboratory, registered dietitians and/or research associates use software to estimate plate waste by viewing pre and post consumption photographs against the reference portion of each food. This method overcomes many of the shortcomings associated with other methods of measuring food intake.

Digital photography allows for rapid acquisition of data with very little inconvenience to participants and allows researchers the opportunity to perform unhurried evaluations of portions sizes from photographs. (Williamson et al., 2003) A backup of these images can then be easily assessed by off-site raters. (Parent et al., 2012). Although this method holds promise for evaluating plate waste and has the potential to translate well to a self-serve salad bar, it is not completely automated and may lead to bias as it relies on trained observers or registered dietitians to evaluate the portion size. Similarly, though digital observation moves the rater's task from the cafeteria to the laboratory, the time required makes it impractical for thousands of samples. Time burdens are further magnified when in-depth nutritional analysis is needed. All these hurdles have led researchers to search for alternatives that can automate the process of data collection and estimate portion size. To reduce bias for portion estimation and automate the process of food estimation, enhancements are needed to supplement the current plate waste methods.

1.4.4 Image Recognition Model

An Image recognition model method is proposed in this study as novel technique for estimating portion size and plate waste. This method employs digital photography but automates the estimation process. By comparing pre and post photographs of a salad plate (i.e., the plate as served and after the participant has eaten), the image recognition model makes estimations of the initial serving size of each food item and amount of food left on plates that can be used to estimate plate waste. Section 2 explains the details of the Digital Image recognition model used in this study.

2 Image Recognition Model

2.1. Image Recognition

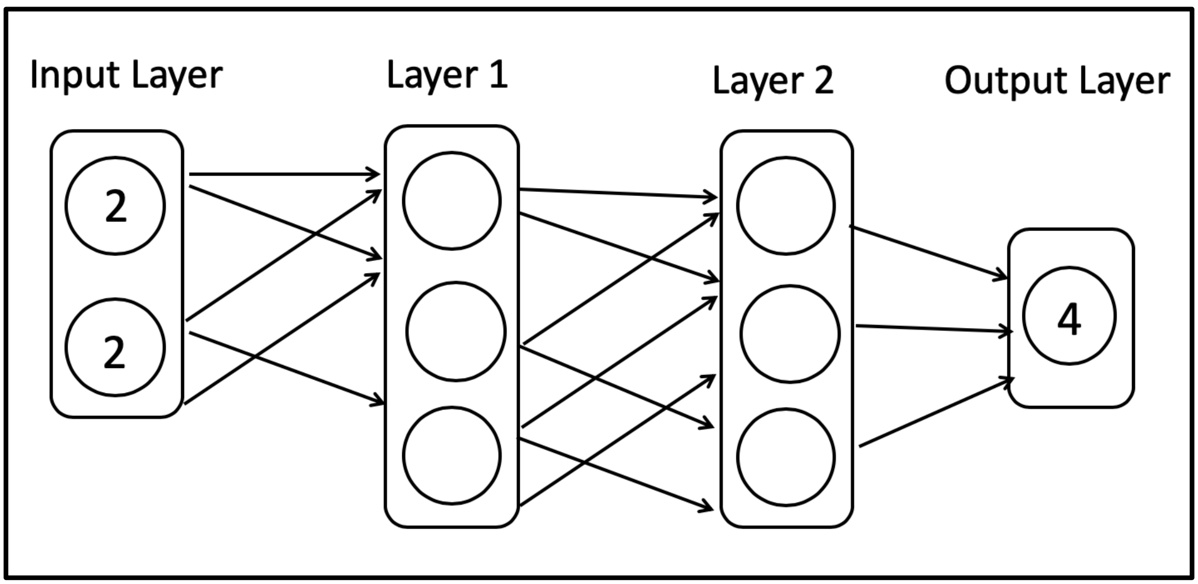
Image recognition is a part of computer vision and a process to identify and detect an object or attribute in a digital video or image. It is the ability for a computer to recognize the photograph and understand what is in the photograph. Using neural network, it is possible to recognize objects and photographs with high accuracy.

2.2 Artificial Neural Network

An Artificial Neural Network (ANN) in simple terms is a biologically inspired computational model, which consists of processing elements (called neurons), and the connections between them with coefficients (weights) bound to the connections. These connections constitute the neuronal structure and attached to this structure are training and recall algorithms. Neural networks are called connectionist models because of the connections found between the neurons (Nikola Kasabov, 1995).

ANN is made up of separate nodes called neurons. The neurons are arranged into a series of groups called layers. Nodes in each layer are connected to the nodes in the following layer. Data flows from the input to the output along these connections. Each individual node is trained to perform a simple mathematical calculation and then feed its results to all nodes its connected to. The neural network takes in a set of input values. Then those values pass through all the following layers. Each node tweaks the value it receives slightly and passes its result to the next node. For example, the neural networks could be used to perform addition. If two values that needs to be added are put into the input layer, it gives the result in the output layer. But neural networks are not limited to doing simple operations like addition only. When many layers are connected and data flows through the entire network, neural networks are able to model complex operations like recognizing objects and images. (Deep learning: Image recognition & nbsp, 2018). Figure 1 shows how an artificial neural network is used to perform simple addition.

Figure 1: How Artificial Neural Works for Mathematical Calculation



2.3 Digital Images

A digital Image is a series of individual color pixels that make up the image. Each color pixel is made of three colors (red, green and blue color channels) that are stored separately. Each pixel is numbered from 0 to 255 that represents the intensity of color at that point with bright points being closer to 255 and the dark points closer to zero. Each color channel is a two-dimensional array of integers with one number of each pixel in the image. Inside of the image file, there are three separate arrays for each color. When three color channels are laid on top of each other, the image appears as three layers deeps and is referred to as 3-dimensional array. To feed an image into a neural network, one input node is needed for every number in the 3D array. For a small image of 256 x 256 pixels (multiplied by the 3 required input nodes) the model would add up to 196 thousand inputs. The number of nodes in the entire neural network will grow into the millions. Thus, processing a standard image requires sending it through a neural network of millions of nodes.

If an image of tomato is passed through the neural network, it generates a label “tomato” because that is the main object that appears in the picture. However, image recognition is not easy as different foods can have various shapes, colors and size. Thus, before the neural network can be used to make classifications like “tomato” or “avocado”, it needs to be trained with several images representative of each class with various shapes and color so as the neural network can recognize these images irrespective of the size and shape, and also when they are present with other foods and background noise. Figure 2 shows how an artificial neural network is used for image recognition.

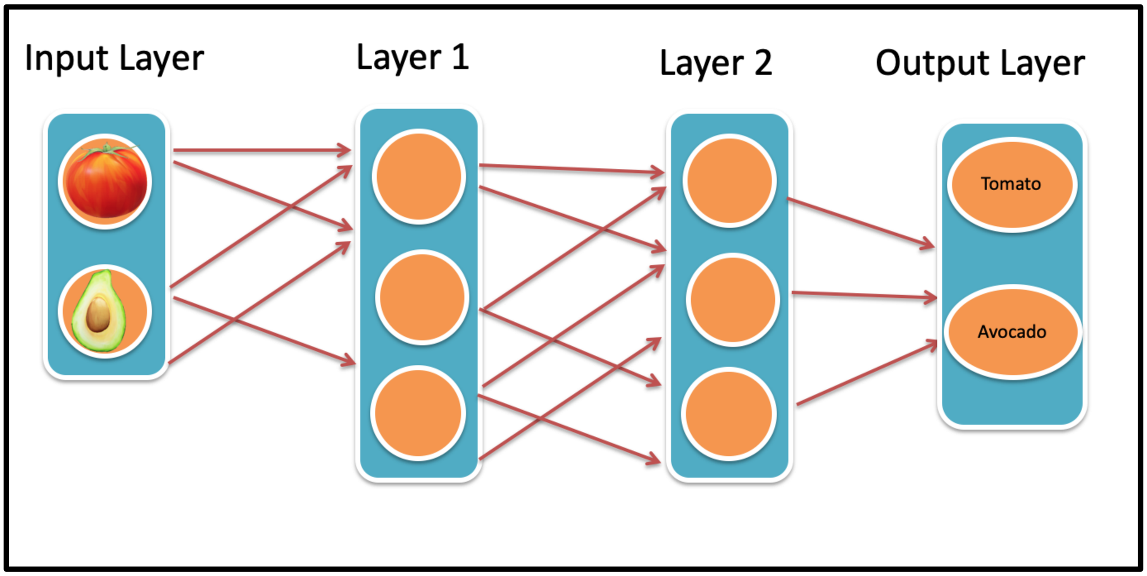


Figure 2: Artificial Neural Network for Image Recognition

2.4 Training Neural Network

If the neural network needs to be trained for carrot, numerous training images needs to be collected. Over 1000 images of carrots are collected and it also needs a large number of images that do not represent carrot. Thus, the neural network can learn to differentiate between food classes. The Food-101(Lukas et al., 2014) dataset contains 101 food categories with seven hundred and fifty training and two hundred and fifty tests images per category. The UEC256 (Kawano & Yanai, 2015) data set consists of two hundred and fifty-six food categories including Japanese and international dishes. Both databases are commonly used to train neural networks for food recognition.

Neural network training is divided into two phases, the training phase and the inference phase. These phases are described in the next sections.

2.4.1 Training Phase

As described above, different images besides carrots need to be used to train the neural network. The network assigns a true match to carrot as one and false match to carrot as zero. After repeating this process over and over with many images, the neural network eventually learns the weight for each node that makes it possible to separate images of carrot from the other images. Figure 3 shows how a neural network is trained with images and Figure 4 shows how a neural network is trained for an image prediction.

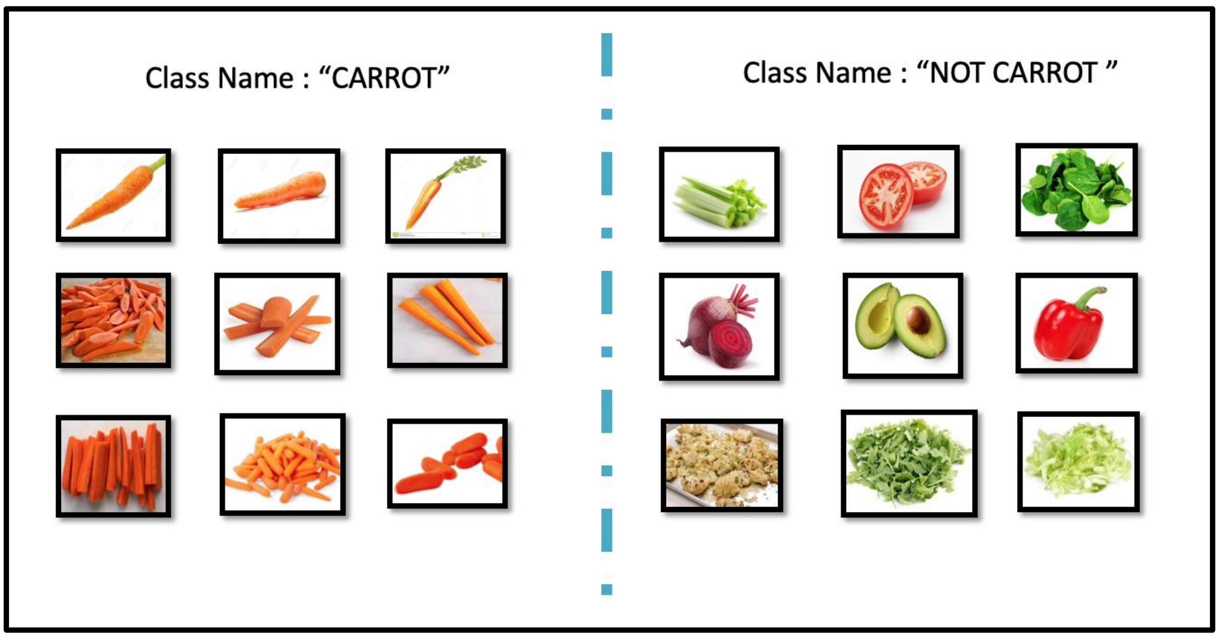


Figure 3: Training a Neural Network with Images

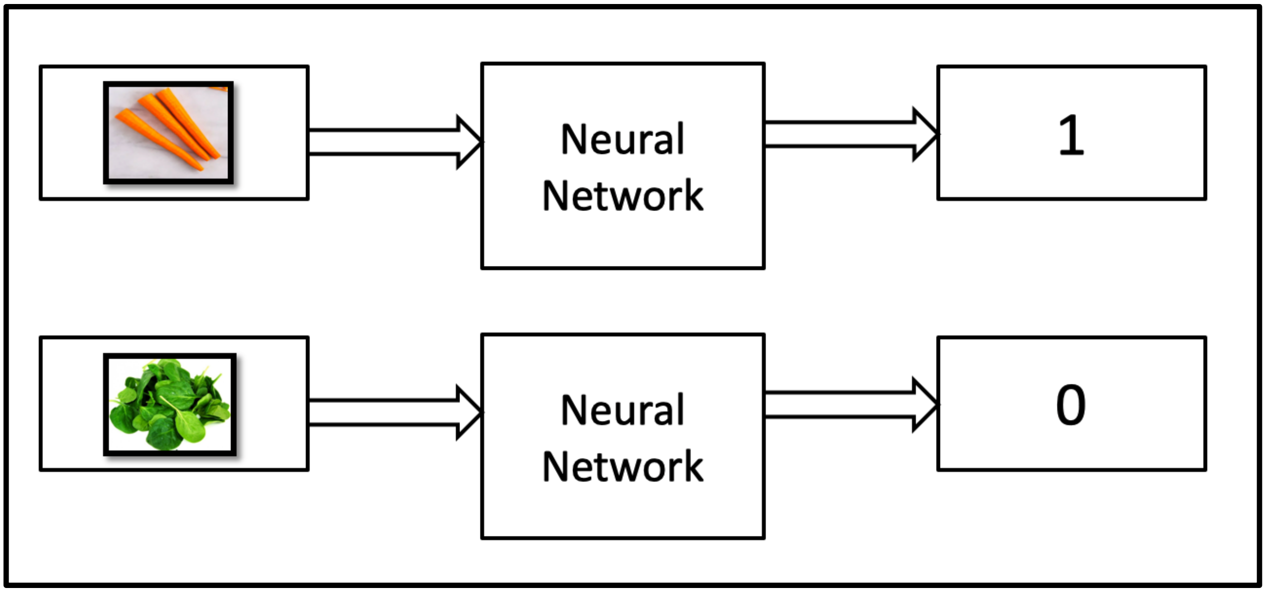


Figure 4: Training neural network for image prediction

2.4.2 Inference Phase

Once the neural network is trained, a new image is passed through the neural network to predict the best guess for the correct answer. This process is called prediction. But instead of generating a zero or one, it gives a floating number between zero and one based on how well the network can determine the food class. If an image of carrot is passed through a neural network, it gives a value of 0.8 and if any other image besides carrot is passed through the neural network, it predicts a number close to zero like 0.04. Figure 5 explains the inference phase of neural network

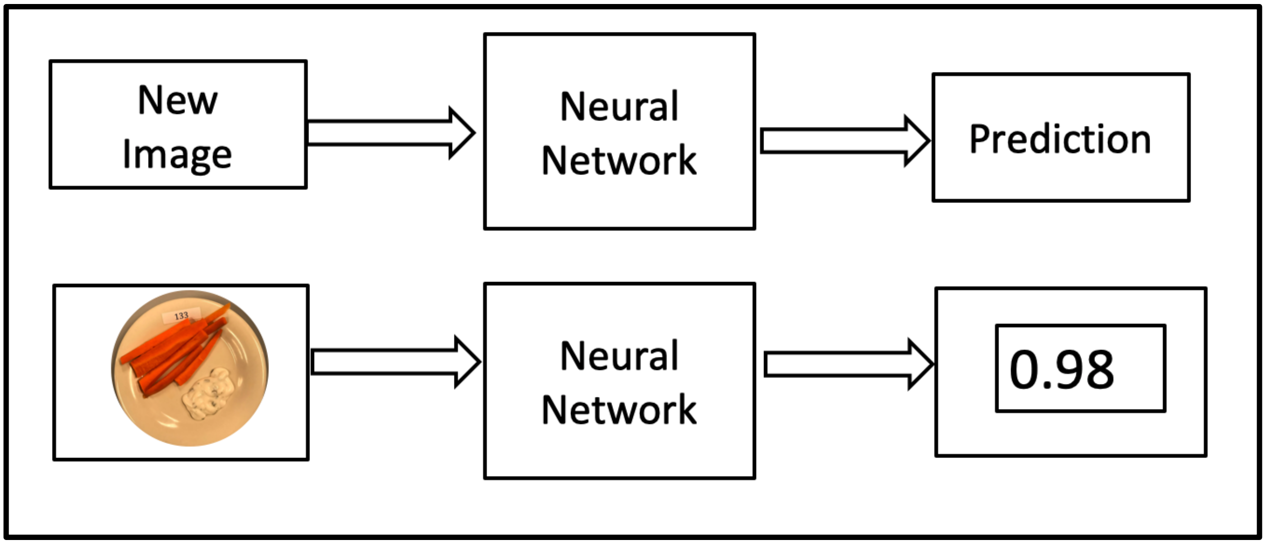


Figure 5: Inference phase of a neural network

2.5 Convolutional Neural Network (CNN)

A Convolutional Neural Network is a class of deep neural network. A neural network can be trained to recognize an image of a carrot, but when the data is not clean and simple, it will be difficult for a neural network to classify the image. If the neural network is trained with pictures of carrots alone that are perfectly centered in the image, the neural network will get confused if it sees anything else. If an image e.g., carrot is not visible or hidden under a layer of other food, the neural network will not be able to make a good prediction. Since the carrot could appear anywhere in the image, the neural network needs to be improved so as it can recognize objects in any position. The solution to this problem is to add a convolutional layer.

Unlike a normal dense layer, where every node is connected to every other node, a convolutional layer breaks apart the image in a special way so that it can recognize the same object in a different position. There are 3 steps to this process.

Step 1: A small window is passed over the image. Each time it lands somewhere, a new image tile is grabbed. This process is repeated until the entire image is covered.

Step 2: In the second step, each image tile is passed through the same neural network layer. Each tile will be processed the same way and a value is saved each time., i.e., the image is turned into an array, where each entry in the array represents whether or not the neural network recognizes that a certain pattern appears at that part of the image.

Step 3: The same exact process is repeated again. But a different set of weights on the nodes in the neural network layers are used. This turns our original array into a 3D array. This 3D array is fed into the next layer. Using this information, the network recognizes which patterns are most important in determining the final output

Adding a CNN layer makes it possible for the neural network to be able to find the pattern no matter where it appears in an image. Normally there are several CNN layers that repeat the process multiple times. CNN helps in narrowing down the image with each layer while still capturing the most important information. By the time it reaches the output layer, the neural network is able to identify whether or not the object appeared. Figure 6 shows the Convolutional Neural Network in Image recognition.

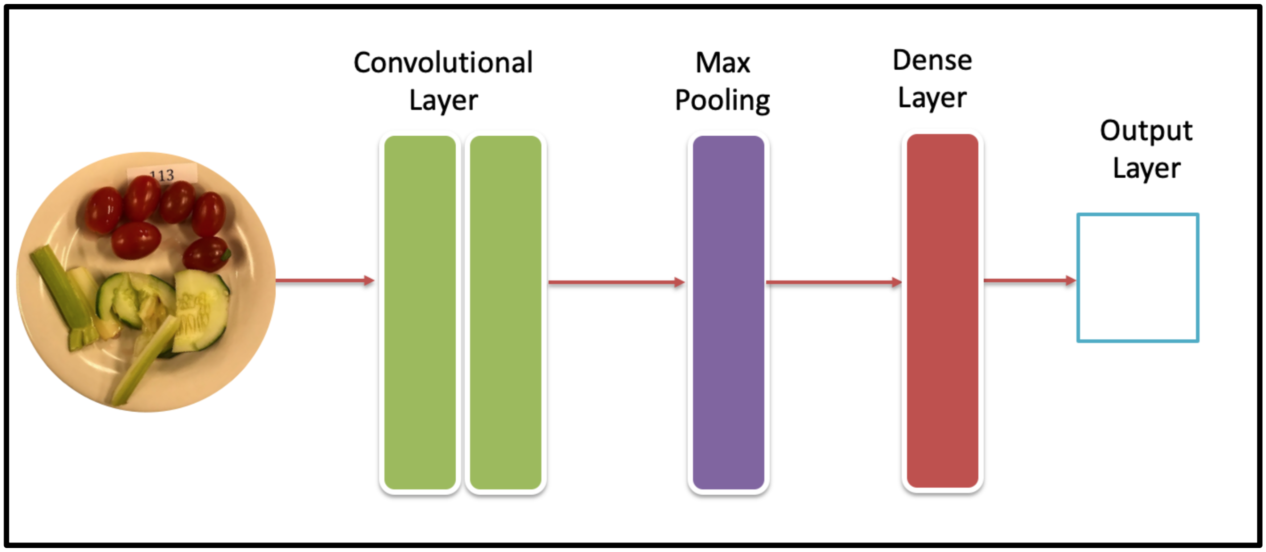


Figure 6: Convolutional Neural Network

2.6 Max Pooling

In order to make the neural network efficient, a technique called max pooling is used. If the filter is looking for a pattern that looks like tomatoes, a ‘zero’ in the grid means that the pattern was not found at all and a ‘one’ means the area was a strong match for the pattern. This information can be passed directly to the next layer, but this makes the neural network inefficient. The idea of max pooling is to down sample the data by only passing on the most important information. Figure 7 shows how max pooling is performed in an image recognition.

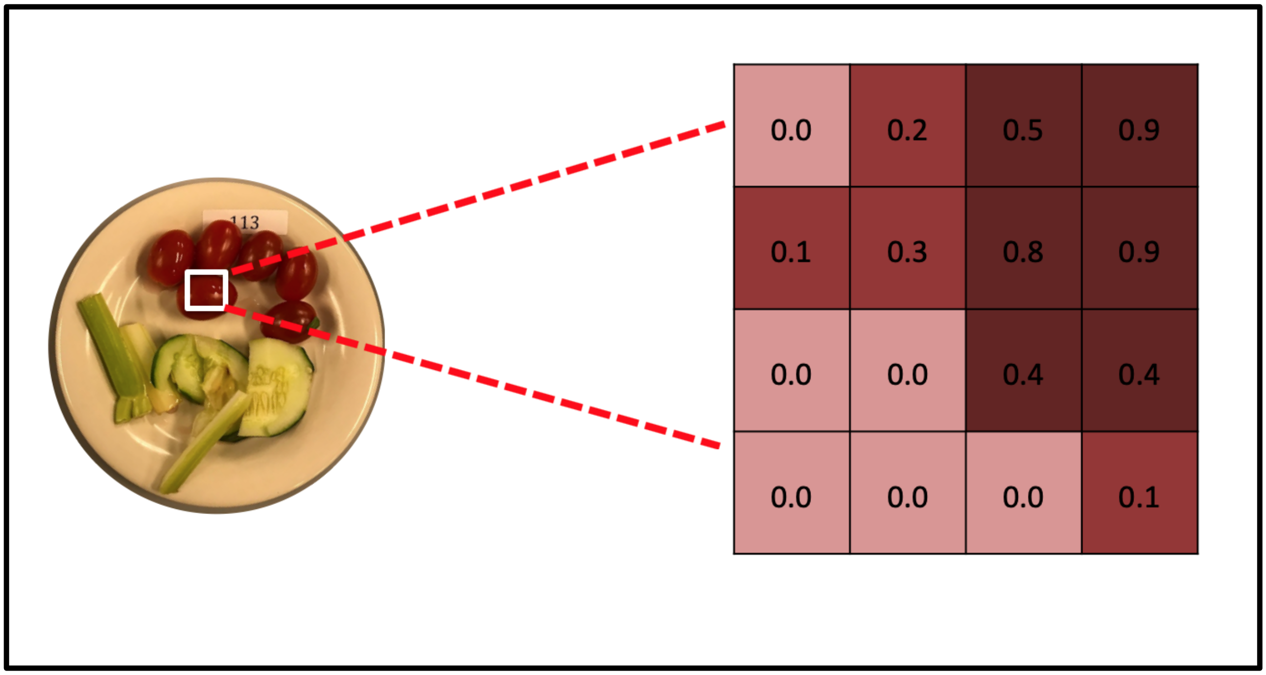


Figure 7: Performing Max Pooling for Food Image Recognition

2.6.1 How Max Pooling Works

Max pooling works by dividing the grid into two by two squares. Within each two by two square, the largest number is retained. If there is a tie, only the first number is retained. A new array is created from the saved numbers. This captures where each pattern is found in image, but now the model is built by using only a fraction (¼) of the data. Figure 8 shows how max pooling works.

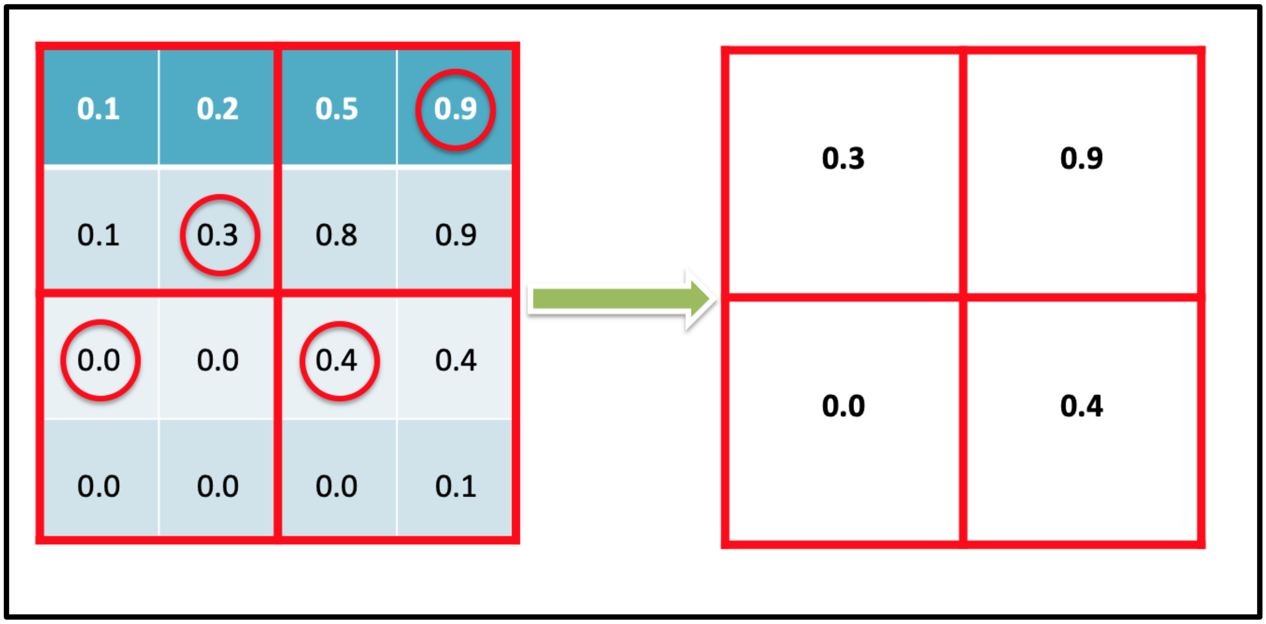


Figure 8: How Max Pooling Works

2.7 Regression

Finally, weight estimations are made by linear regression from the convolutional neural network. This regression layer at the end is fine tuned to predict weights of the food.

3 RATIONALE & HYPOTHESIS

Previous studies have shown that the direct weighing method is the most accurate method for calculating plate waste (Adams et al., 2005; Cohen et al., 2013; Jansen & Harper, 1978) and digital imagery assessment presented as the most time efficient method for data collection. Thus, we hypothesize that the use of more advanced technology may provide a valid, reliable and time-efficient strategy to measure children's plate waste and hence the food intake.

Our approach was to semi automate the process of data collection using digital imagery and using estimated weights from an image recognition model and validate the accuracy of plate waste against the direct weighing method. At first, pre and post consumption photos are captured, then a digital image recognition model was developed to identify food classes and to estimate food weights. Aggregate plate waste is calculated as a percent of what was self-served (i.e., (Post Weight /Pre-Weight) ×100). The specific objectives of the study are divided in two phases. Phase I is the training phase and Phase II is the testing phase.

3.1 Objectives

3.1.1 Phase I

1) To test feasibility & validate the machine learning model (SRI International, Princeton, NJ) to identify

a. Pre trained food classes

b. Estimate pre and post plate weights at the PACS self-serve salad bar

3.1.2 Phase II

To validate the accuracy of the machine learning model as a tool to

a. Quantify aggregate vegetable waste

b. Compare aggregate vegetable waste generated by the model to aggregate vegetable waste calculated using the gold standard plate “weighing method”

4 METHODS

The study was divided in two phases. Phase I is the training phase and Phase II is the analysis phase. Data were collected in two phases.

4.1 Phase I: Training

In Phase I, data was collected from the self-serve salad bar at Philip's Academy Charter School (PACS) in October 2017. Participants included students from 5th through 8th grades. All students present on that day were eligible to participate in the study. Each plate was coded with a three-digit unique code and was arranged at the salad bar before the lunch hour. The table with digital weighing scale and the smartphone was placed directly after the salad bar to capture pre and post consumption photos and weights.

Each student picked a three-digit coded plate and filled the plate at the self-serve salad bar that was comprised of spinach, tomato, edamame, veggie rice, lettuce, celery, carrot, guacamole and dressing. Visual inspection was conducted in order to ensure the three-digit code was visible before taking the photos and physical weights. Five images at varying angles were taken in a panoramic motion and physical weight was recorded. After the lunch hour, students were encouraged to bring the plates back to the data collection station or drop the plates in a designated area to capture the post consumption images and weights. A total of eighty-four real world salad plate images (before and after) and weights were recorded from forty-two students.

In order to train the model, additional mock salad plates were created after the lunch hour using the combination of the same nine food classes served on the salad bar. A total of three hundred mock salad plate images and weights were collected. Each plate was labelled with a three-digit unique code.

The training phase had a data set comprised of eighty-four real world images and three hundred mock images. For each image, the three-digit code followed by "B" or "A" depicting before or after, food classification and recorded weights was extracted and transformed into a CSV file in a mutually defined format with SRI International. This CSV file was then loaded into the pre trained model by SRI international. Figure 9 shows the format of CSV file used for training the image recognition model.

```
201-1.B.jpg,0.12,spinach,tomato,edmame,carrot,celery,blackbeans,cauliflower,veggie-rice
201-1.A.jpg,0.055,spinach,tomato,edmame,carrot,celery,blackbeans,cauliflower,veggie-rice
202-1.B.jpg,0.115,spinach,tomato,edmame,carrot,celery,blackbeans,cauliflower,veggie-rice
202-1.A.jpg,0.045,spinach,tomato,edmame,carrot,celery,blackbeans,cauliflower,veggie-rice
203-1.B.jpg,0.1,spinach,tomato,edmame,carrot,celery,blackbeans,cauliflower,
203-1.A.jpg,0.035,spinach,tomato,edmame,celery,blackbeans,cauliflower,,
204-1.B.jpg,0.05,spinach,tomato,edmame,carrot,celery,blackbeans,veggie-rice,
204-1.A.jpg,0.01,spinach,edmame,blackbeans,veggie-rice,,,,
205-1.B.jpg,0.07,spinach,tommato,edmame,celery,cauliflower,veggie-rice,,
205-1.A.jpg,0.02,spinach,edmame,cauliflower,,,,,
206-1.B.jpg,0.055,spinach,tomato,edmame,blackbeans,cauliflower,veggie-rice,,
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207-1.B.jpg,0.05,spinach,tomato,carrot,blackbeans,cauliflower,veggie-rice,,
207-1.A.jpg,0.005,veggie-rice,,,,,,,
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209-1.A.jpg,0.035,tomato,edmame,celery,blackbeans,veggie-rice,,,
```

Figure 9: CSV file for training the image recognition model

Training data comprised of three hundred and fifty-four images (92%) that was fed into a model by SRI International that had been pre trained by them using the Food 101, Food-Web-G and UEC256 data sets (Kaur & Sikka, 2017; Lukas et al., 2014; Kawano & Yanai, 2015). The model was trained to obtain two outcomes, i.e., predicting food classes and weights. The model was tested for feasibility of predicting classes and weights using the thirty images (8%) of the training data set. Figure 10 shows the trained SRI model and its deliverables.

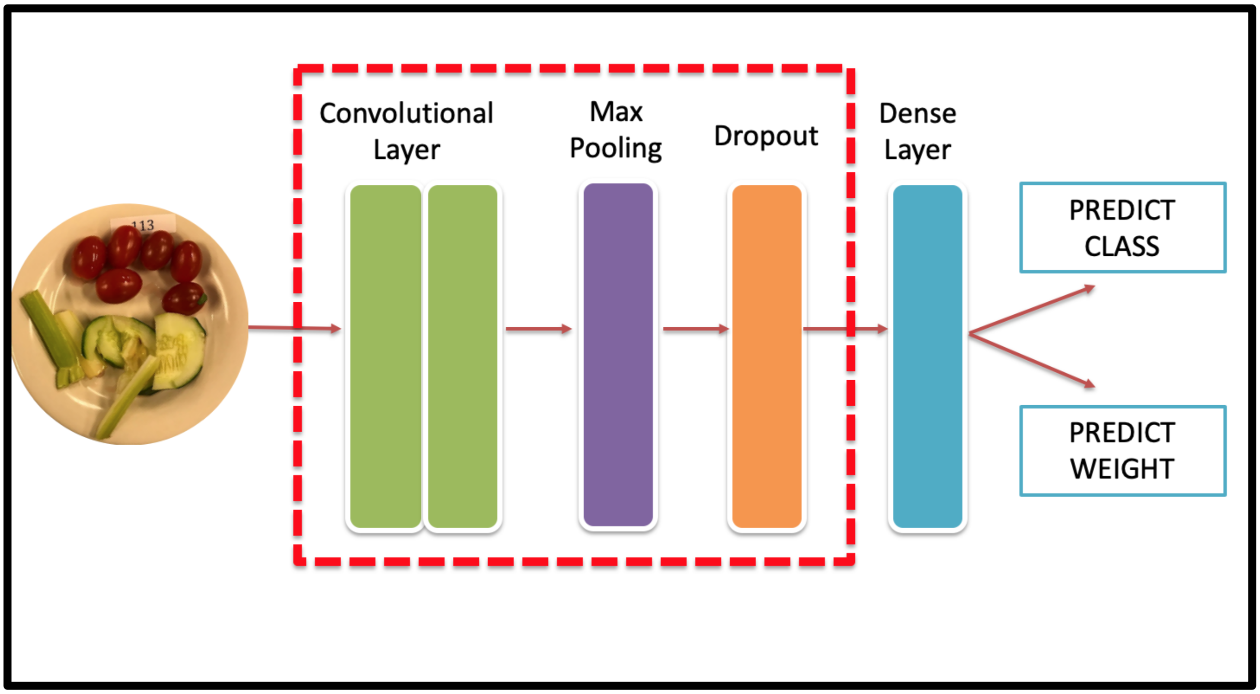

Figure 10: Trained SRI model and its deliverables

4.2 Phase II: TESTING

After the model was tested for feasibility, data was collected in February 2018. The objective was to compare the image recognition model against the gold standard weighing method for plate waste analysis. On the day of data collection, a presentation was given to the students from 5th through 8th grade at the assembly hour creating awareness about plate waste and the methodology used to collect data to estimate plate waste in the salad bar. Figure 11 shows the visual aid used in the study for students.

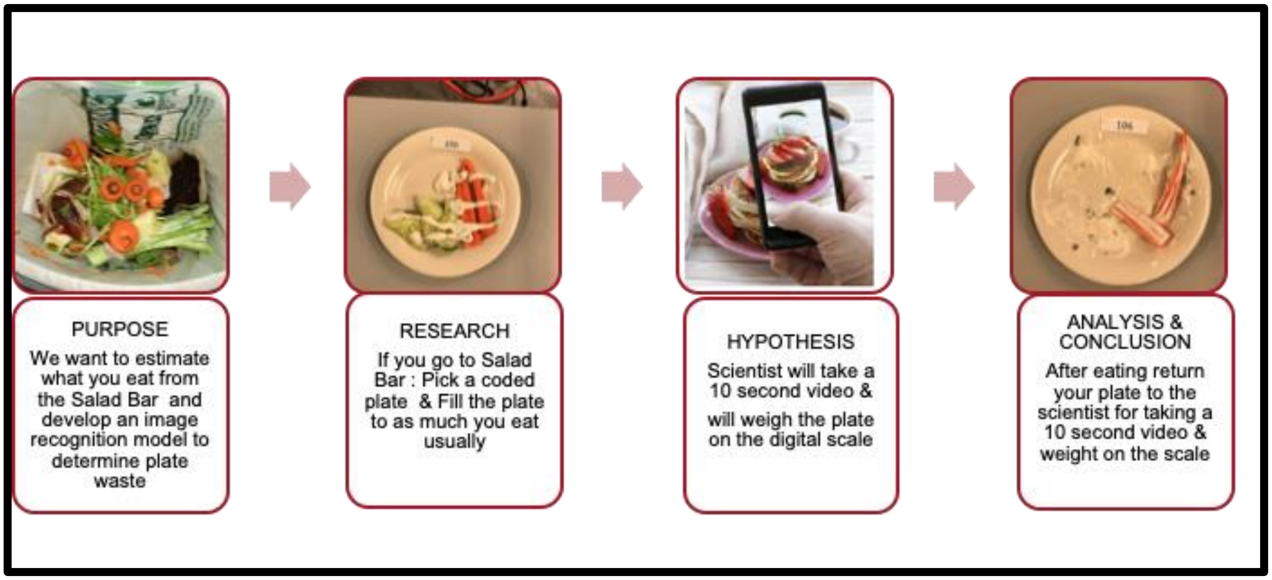

Figure 11: Visual aid used in the study for students

The data collection procedure was similar to phase I. However, instead of collecting images in panoramic motion, eight to ten second MOV videos were captured in a panoramic motion and the physical weights were recorded for pre and post consumption. Each MOV file was converted to a series of images using “ffmpeg” command line tool (FFmpeg developers).

The top view image was selected and cropped manually to reduce any background noise. Phase II had a total of eighty-two images from forty-one students from 5th,7th and 8th graders. There was an overlap of the students who participated in Phase I and Phase II. However, this could not be tracked as student identity was not captured in both the phases. For each image, the three-digit code followed by “B” or “A” depicting before or after, food classification and recorded weights was extracted and transformed into the same CSV file format as the training data set and was shared with SRI International. This CSV file was then loaded into the extended model created by SRI international from the training phase.

Data were analyzed to compare the image recognition model against the gold standard weighing method for predicting pre, post weights and plate waste. The plate waste was calculated as a percent of what was self-served (i.e., (Post Weight /Pre-Weight) ×100) for recorded weights and compared it against the model prediction for weights. Figure 12 shows the flowchart for data collection.

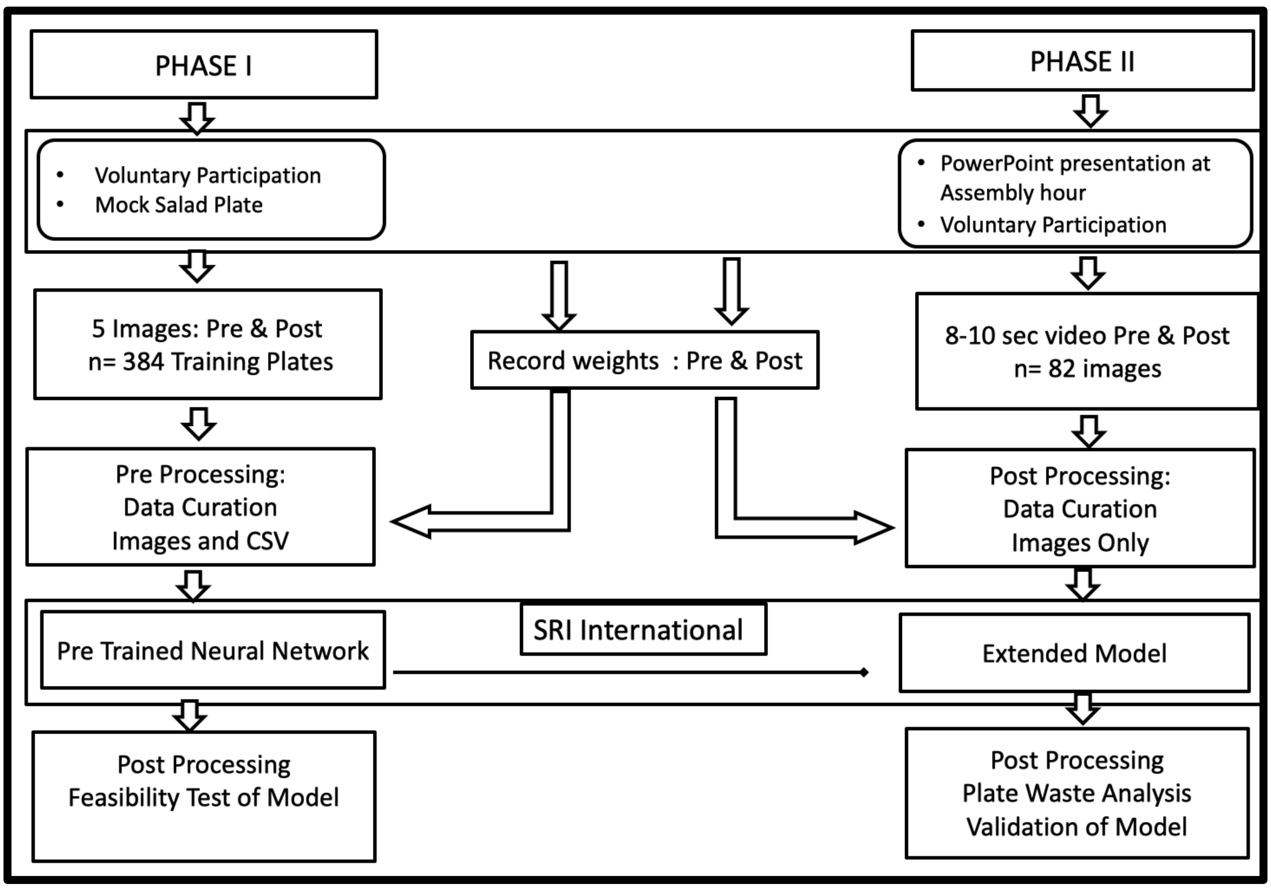

Figure 12 Flow chart of data collection

5 RESULTS

5.1 Phase I: Phase I, training data was tested for accuracy of the image recognition model for predicting food classes and weights.

5.1.1: Predicting Food Classes

We evaluated our model accuracy on our data set consisting of three hundred and eighty-four images comprised of nine predefined food classes. By using randomly chosen images for training and testing, the image recognition model achieved overall classification accuracy of 85.7% of predicting nine food classes. Table 1 and Figure 12 show the average classification accuracy, i.e., the percentage of the test images of each class correctly classified.

Sr. No	Food Items	Classification Accuracy (%)
1	Spinach	97.9
2	Tomato	73.7
3	Edamame	87.7
4	Carrot	97.9
5	Celery	65.3
6	Black beans	83.6
7	Cauliflower	81.6
8	Veggie Rice	83.6
9	Guacamole	100
10	All Classes	85.7

Table 1: Food Class Prediction Accuracy in Phase I

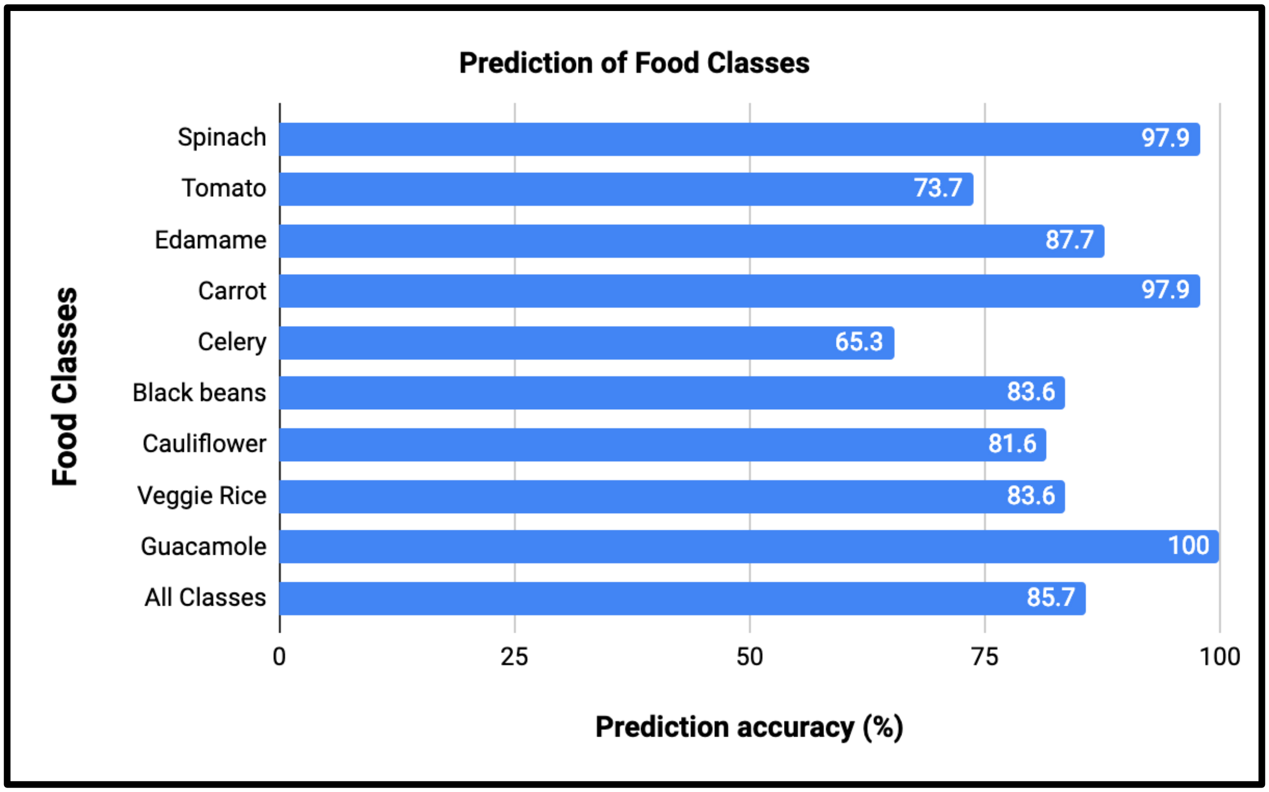

Figure 12: Food Classes Prediction Accuracy in Phase I

5.1.2: Predicting Weights

Training data was analyzed to determine if the extended model of SRI International was feasible for predicting food weights in addition to food classification. The data were tested for normality and results showed that recorded and predicted weights data were not normally distributed. The data were then transformed to log values. The Wilcoxon signed-rank test which is the nonparametric test equivalent to the t-test was used. The feasibility of the model was tested by performing a Wilcoxon test between the recorded weights and predicted weights. The mean rank for recorded pre weight was (1.61 g ± 0.43 g) and predicted weight was (1.01 g ± 0.99 g) The feasibility results suggested that there was a significant difference between the recorded and predicted weights (p=0.009).

Table 2 shows mean rank difference between recorded and predicted weights in Phase I.

		Mean Rank Difference ± SD		p value
	n	Recorded	Predicted	
Weights (g)	30	1.61 ± 0.43	1.01 ± 0.99	0.009

Table 2: Mean rank difference between recorded and predicted weights in Phase I

The recorded mean pre weight was 58.6 g ± 39.8 g and predicted weight using image recognition model 53.3 g ± 71.7g. Table 3 shows mean plate weight in grams for recorded and predicted weights in Phase I.

		Mean Plate Weight + SD		p value
	n	Recorded	Predicted	
Mean Plate Weights (g)	30	58.6 +39.8	53.3 + 71.7	0.7455

Table 3: Mean Plate Weight (g) between recorded and predicted weights in Phase I

5.2: Phase II

Data was analyzed to compare the model against the gold standard weighing method. Due to the non-normal distribution of the data, it was transformed to log values and the nonparametric Wilcoxon signed rank test was performed for comparison. Non-significant findings in this test support the null hypothesis (i.e., no differences between recorded and predicted values) in line with our expectations.

5.2.1: Pre-Weights

The mean rank for recorded pre weight was (1.63 g + 0.45 g) and predicted weight was (1.73 g + 0.22 g). The Wilcoxon signed-rank test showed that weight predicted by the model did not elicit a statistically significant difference as compared to manually recorded weight ($p = 0.341$). Recorded mean pre weight was 63.4 g + 46.7 g and predicted weight using the image recognition model was 59.9 g + 25.9 g.

5.2.2: Post Weights

The mean rank for recorded post weight was (0.62 g + 0.77 g) and weight predicted by the image recognition model was (0.63 g + 0.80 g). Wilcoxon signed-rank test showed that median of difference between the recorded and predicted weight equals zero i.e. no statistically significant difference observed between the recorded and predicted post weight by the model (p=0.619). Recorded mean post weight was 15.2 g ± 22.9 g and predicted weight using image recognition model 18.1 g ± 26.8 g.

5.2.3 Plate Waste (Pre-Weight vs Post Weight)

The plate waste data was compared between plate waste calculated using pre and post recorded weights and aggregate plate waste calculated using the pre and post predicted weights. The mean rank for recorded plate waste was (0.68% ± 0.83%) and plate waste determined by the predicted weights by the image recognition model was (0.72% ± 0.91%). The Wilcoxon signed-rank test showed no statistically significant difference (p=0.177).

Mean plate waste was 20.5% ± 29.4% using the recorded weights and 31.6% ± 55.4% using the weights from the image recognition model.

Table 4 shows mean rank difference between recorded and predicted weights (grams) and plate waste (%) (Table 5 shows the mean plate weights (grams) and plate waste (%) between recorded and predicted weight

		Mean Rank ± SD		p value
	n	Recorded	Predicted	
Pre-Weight (g)	41	1.63 ± 0.45	1.73 ± 0.22	0.341
Post Weight (g)	41	0.62 ± 0.77	0.63 ± 0.80	0.619
Plate Waste (%)	41	0.68 ± 0.83	0.72 ± 0.91	0.177

Table 4: Mean rank difference between recorded and predicted weights (g) and plate waste (%) in Phase II

		Mean + SD		p value
	n	Recorded	Predicted	
Pre-Weight (g)	41	63.4 + 46.7	59.9 + 25.9	0.6720
Post Weight (g)	41	15.2 + 22.9	18.1 + 26.8	0.3177
Plate Waste (%)	41	20.5 + 29.4	31.6 + 55.4	0.0668

Table 5: Mean plate weights (g) and plate waste (%) between recorded and predicted weight

6 DISCUSSION

6.1 Phase I

6.1.1. Food Class Prediction Accuracy

The result of the study supports the feasibility of the image recognition model for predicting food classes and weights. High prediction accuracy of the food classes in Phase I clearly shows that the model is capable of predicting the nine predefined salad food classes accurately (85.7%). Zhang et al developed mobile food recognition system, “Snap-n-Eat” achieved over 85% accuracy for detecting 15 categories of foods comprised of white and red meat, fruits and vegetables. The training data used in our study was a smaller data set of three hundred and eighty-four images as compared to Snap-n-Eat that had approximately two thousand training images for fifteen categories with one hundred to four hundred images for each category However, our data suggests that our food prediction accuracy results are comparable to this study since the data was manually collected in both of them. (Zhang et al., 2015). Another study that leveraged the freely available web-based Food 101 dataset that consists of one hundred and one food categories and the UEC256 data set that consists of Japanese and International dishes, achieved a food classification accuracy of 76.2% (Kaur Parneet, & Sikka Karan, 2017). Our findings are comparable to the study of Zhang et al. (2015) as images were manually curated in both of them to reduce background noise and improve accuracy. Although, an extensive image data set is critical for developing the image recognition model, our study had limited training images due to time constraints as compared to Kaur et al, (Kaur & Sikka, 2017). Celery achieved the lowest classification accuracy (65.3%) compared to other food classes. Further examination revealed that celery was classified as carrots due to similar shape. Limited training data set for training also explains the discrepancy in food class prediction and corresponding accuracy. In future image recognition must seek to address these outliers in measurements by using adequate training images.

6.1.2 Weight Prediction Accuracy

Contrary to our hypothesis, examination of mean rank differences in weights between the image recognition model and recorded weights indicated that there was a significant difference in the recorded and predicted weights. The discrepancy in the weight estimations could be attributed to several factors such as the limited amount of data used for testing feasibility of the training data set (8 % images from the training data). Our model was also limited to using the best of five angles of the captured image. The model also detected lot of background noise in the images. Thus, in order to improve the accuracy of the digital image recognition model for weight estimations, MOV files were captured instead of images in a panoramic motion, and the best view image from a series of images obtained from the MOV file was cropped to eliminate background noise in Phase II. An extensive image data set is critical for an image recognition model because it enables the learning of more general features and therefore helps combating overfitting, which is a common occurrence in machine learning, where the model describes random noise instead of learning generalizable knowledge. Due to time constraints, limited training data was captured. However, it may be possible to improve the accuracy of model prediction by providing additional training data as a future work.

6.2 Phase II

Examination of mean rank differences in weights between the image recognition model and recorded weights using MOV files revealed no significant difference in pre and post weights and plate waste estimations. Although digital imagery has been used for measuring plate waste in salad bars in a handful of prior investigations (Bean et al., 2018;Todd et al., 2017), this study was the first to compare an image recognition model against the gold standard weighing method for estimating plate waste. Our findings strongly support the accuracy of an image recognition model in the analysis of plate waste from a salad bar.

Wilcoxon signed rank showed that there were no significant differences for pre, post and plate waste using recorded and predicted weight. Although, the model underestimated the mean pre weights by 3.5 g and overestimated the mean post weights 2.9 g, this difference corresponds to <1Kcal, suggesting negligible influence on nutritional estimates.

Our results are comparable with a laboratory-based study that examined the reliability and validity of digital imagery for determining starting portions and plate waste of self-serve salad bar vegetables using 30 mock salad plates with seventy-three vegetables compared with manual weights (Bean et al, 2018). In that study, digital imagery assessments were not significantly different from measured weights for estimating overall vegetable starting portions or waste; however, digital imagery assessments slightly underestimated starting portions (by

3.5 g) and waste (by 2.1 g) of leafy greens and underestimated plate waste by 3.1% for vegetables. In contrast, another laboratory-based validation study that had a total of 60 test meals consisting of 10 different portion sizes from six different university cafeteria menus reported overestimation of 4.8 g of fruits and vegetables from digital imagery estimation as compared to weighed estimates (Williamson et al., 2003) Taylor and colleagues (2014) tested the reliability and validity of digital imaging (DI) and digital imaging with observation in assessing children's fruit and vegetable consumption during school lunch and found that digital imagery assessment overestimated consumption of salad green by 3 g. Although we compared our results with these studies, an important point to note here, that digital imagery estimation is biased due to manual errors as compared to our image recognition model that is completely automated and eliminates the bias from the user.

The mean plate waste analyzed using gold standard weighing method and model prediction was 20.5% and 31.6% respectively in our study. A similar study that was conducted to measure children fruit and vegetable consumption in the elementary school cafeteria using digital food image analysis (DFIA) to measure its validity against digital observations found no significant difference between the two estimations (digital food image analysis vs digital observations) with an average difference of 5.7 g for vegetables. (Todd et al., 2017).

Our results are also aligned with the plate waste study that was conducted in a middle school setting to examine if the location of the salad bar had any impact on fruit and vegetable waste using the direct weighing method. It was found that students with salad bar located outside the serving line wasted less fruits and vegetables compared with those with salad bars inside the line (30 % vs 48%) (Adams et al., 2016) Another study that determined fruit and vegetable school lunch waste in an elementary school participating in a farm to school program found that mean fruit and vegetable waste from entrees was 27 %. (Berezowitz et al., 2015). However, our results cannot be representative of the plate waste as compared to these studies due to the limited sample size.

We also compared our results with other plate waste studies that used the weighing method to compare it against the other methods of measuring plate waste in school. The Bland Altman plot method is commonly used in plate waste studies to measure agreement between two methods of measuring plate waste. It is based on the quantification of the agreement between two quantitative measurements by studying the mean differences and constructing limits of agreement. The bias is computed as the value determined by one method minus the value determined by the other method. The bias between the two test is measured by mean of differences. The average of differences (bias) should be close to zero. If it is not close to zero, this indicates that two assay methods are systematically producing different result (Giavarina, 2015).

Liz Martins et al. (2014) found that mean plate waste was 27.5% and found higher correlation between visual estimation and weighing method for estimating plate waste in primary school lunch. However, the Bland Altman plot analysis did not show agreement between the two methods and showed significant bias in the conversion of the visual waste estimation to actual waste, being overestimated by an average of 8 g (Liz Martins et al., 2014). Williamson et al. (2003) compared digital photography methods, weighed and visual estimation of portion sizes in 60 test meals comprised of 6 different meal categories and reported comparable results between the digital photography method and the two other methods (overall bias less than 1.5 g). (Williamson et al., 2003) Since the Bland Altman plot assumes normal distribution, it could not be applied in our study due to non-normal distribution in the data. Nevertheless, our results are comparable to these studies comparing different methods of plate waste estimation against the gold standard weighing method.

The strength of this research is related to the weighing of each plate before and after and being able to automate the process of portion estimation. Although digital imagery assessment is thought to be reliable tool, it is not completely automated and may be biased as it relies on trained observers to evaluate the portion size. Our study was the first one to automate the process of food estimation using an image recognition model to quantify vegetable waste in a school environment and to compare it against the gold standard weighing method in a self-serve salad bar.

7 LIMITATIONS

In light of these findings, it is important to note limitations to the study. A small data set was used for training the image recognition model which influenced the corresponding ability of the model to predict the food classes it was trained on. Given the sample limitations and limited training data, the current study could not assess whether a consistent pattern of over or underestimation existed. In addition to that, the model can only estimate the aggregate weight of salad on the plate and cannot predict individual food items on the plate. Also, the study did not include the estimation of portions or waste from the salad dressing. Due to time constraints of the short lunch break at the school, some post-weight plates could not be measured, and data was not captured if the students took a second serving of salad. Data from sixth grade students could not be captured in Phase II as they were out on a field trip and were not available on the day the data collection was planned. It is also important to note that children's tendency to play with food and exchange plates between them could influence plate waste data.

8 CONCLUSIONS

The main findings from this study were that the image recognition model we developed was feasible and accurate for identify food classes and quantifying vegetable plate waste in a self-serve salad bar in a middle school and did not differ significantly from the gold standard weighing method. This study supports the use of a digital image recognition model as a valid tool to semi automate data collection and estimate food waste. The next step in this research will be to further modify the image recognition model, especially on images with added noise and obstructions. To classify images with multiple foods, additional food classes could be trained and can be used as an input in the existing recognition model. This may have potential applications in estimating food components other than vegetables and would be valuable for estimating macro and micro nutrients. It is also important to determine if this image recognition model could be replicated to estimate food intake and waste in other environments and in a larger study sample.

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