Point2Volume: A Vision-based Dietary Assessment Approach using View Synthesis

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Abstract—Dietary assessment is an important tool for nutritional epidemiology studies. To assess the dietary intake, the common approach is to carry out 24-hour dietary recall (24HR), a structured interview conducted by experienced dietitians. Due to the unconscious biases in such self-reporting method, many research works have proposed the use of vision-based approaches to provide accurate and objective assessments. In this paper, a novel vision-based method based on real-time 3D reconstruction and deep learning view synthesis is proposed to enable accurate portion size estimation of food items consumed. A point completion neural network is developed to complete partial point cloud of food items based on a single depth image or video captured from any convenient viewing position. Once 3D models of food items are reconstructed, the food volume can be estimated through meshing. Compared to previous methods, our method has addressed several major challenges in vision-based dietary assessment, such as view occlusion and scale ambiguity, and it outperforms previous approaches in accurate portion size estimation.

Index Terms—Deep learning, point cloud completion, 3D reconstruction, volume estimation, dietary assessment

I. INTRODUCTION

A recent National Health Service (NHS) survey [1] disclosed that the proportion of adults in England who were obese or overweight was 26% and 36% respectively. Unhealthy eating habits, which include nutritional imbalance and excess calorie intake, are the main factors which lead to obesity [2]. Due to the raising awareness of chronic diseases, increasing population pay more attention to their daily food intake. Previous studies indicated that commonly used dietary assessment techniques, such as 24 hour dietary recall (24HR), can effectively help people investigate into their dietary behaviour, and enable targeted interventions to address the underlying health problems, including Type 1 diabetes (T1D) [3]. In 24HR, participants are required to recall the complete profile of the food items eaten in the last 24 hour and estimate the respective portion size by naked eyes. To estimate the portion size, however, it relies heavily on individuals’ subjective perception which could be highly biased and inaccurate. It is for these reasons that various objective vision-based methods, ranging from model-based [4], [5], stereo-based [6], depth camera based [7] and deep learning approaches [8], have been proposed. While these approaches present reasonable accuracy in portion size estimation, there still exist several key challenges such as view occlusion and scale ambiguity. Also, another concern is that current approaches require participants to take images from different viewing angles (in 360°) before eating, which in turn complicates the process and is not able to be embedded on wearable devices for long-term health monitoring. With the technological advancements in depth sensing, various existing mobile devices are already equipped with 3D cameras. Inspired by [9], a novel vision-based dietary assessment approach based on deep learning view synthesis and depth sensing technique is proposed in this work. This approach aims to address the key problems, such as view occlusion and scale ambiguity, in volume estimation by combining the merits of artificial intelligence and depth sensing capabilities. In using such approach, the food volume can be estimated precisely with a single depth image or a video captured from any convenient position which in turn facilitates the implementation of pervasive dietary monitoring on wearable devices. The main contributions of this paper can be summarized as follows: (1) Two network architectures UNet and VNet are proposed to complete the partial point clouds due to view occlusion and estimate the actual volume (cm³) of 3D models respectively. Both of these networks take raw point cloud as input. (2) A novel data augmentation method is developed to enlarge the dataset of 3D models using linear latent interpolation to ease the network convergence. (3) Point cloud pre-processing techniques are developed to facilitate volume estimation. (4) A new 3D food dataset consisting of 4k models with actual volume labelled is constructed to train and evaluate the proposed volume estimation approach in the wild. (5) The generalization abilities of the point completion networks in handling food items with previously unseen viewing angles, portion size and shape geometries are compared with previous network architectures. (6) A new vision-based dietary assessment approach is developed by combining real-time 3D reconstruction and deep learning view synthesis.

II. RELATED WORK

A. Volume Estimation Approaches

With the advances in computer vision, several vision-based approaches have been developed to address the problem of
portion estimation. Specifically, they can mainly be categorized into model-based and stereo-based approaches. Model-based approach estimates the portion size by matching the input of the food items with the pre-built 3D food templates. For example, a previous work by [4] developed a virtual reality method by using pre-constructed 3D food models with known portion size to superimpose onto the image. This technique requires users to translate, rotate and scale the models until the contour of the templates matches with the food items. The accuracy of their proposed method in volume estimation can achieve 79.50% on average (across the food items examined by their research team in the wild). Similar works have also been proposed in [10]. However, model-based method does not possess the generalization ability which hinders the approach in handling objects with irregular shapes and previously unseen objects. Besides, it always requires a certain level of user inputs such as rotating, shifting and scaling of the pre-built 3D models manually to match with the food images. To address this problem, some research studies proposed to use Structure from Motion (SfM) technique to reconstruct the 3D models. SfM-based approach relies heavily on feature points matching between multiple images, estimates the camera positions and makes use of the extrinsic camera parameters to re-project the feature points from image to camera coordinate. This important property facilitates the volume estimation of food items which are of irregular shape so that a wider range of food items can be estimated automatically without any manual intervention and a large-scale model library. Another 3D reconstruction technique which has been extensively used is Simultaneous Localization And Mapping (SLAM). The difference between SfM-based and SLAM-based 3D reconstruction technique is that SLAM-based approach estimates camera motion and reconstruct 3D models in real-time. In [6], the authors developed a real-time 3D reconstruction method to estimate the food portion size. This proposed technique can achieve around 83% accuracy examined with similar food types captured in the wild. Despite the promising estimation results as mentioned in SfM-based and SLAM-based approaches, there are still several challenging problems unresolved. For instance, they require users to capture multiple images from different viewing angles (normally in 360-degree) during eating, which could be considered as tedious and impractical. Furthermore, it requires feature points extraction and matching. For those food items with smooth surface or less significant texture, feature points cannot be extracted effectively, which leads to failure in loop closure and 3D reconstruction. Most importantly, reference objects such as fiducial markers are often required to be placed next to the food items for accurate estimation which makes the whole dietary assessment process inconvenient.

B. Deep Learning in Volume Estimation

In recent years, several research works tried to use deep learning to assess dietary intake. One of the reasons for using such approach is that the scale of the monocular RGB image can be learned implicitly from global cues of the environment without using any intrinsic and extrinsic parameters, which indicates that reference objects or feature matching between frames can be removed. In [11], convolutional neural network (CNN) has been applied to a single RGB image to infer the depth image and estimate the food volume through 3D voxelization. With the voxel representation, the portion size of each labelled item can be estimated respectively. Their model is pre-trained based on the NYU v2 RGBD dataset and fine-tuned using a self-collected dataset named as GFood3d (captured by RealsenseF200 depth camera) with different kind of meals from Google cafes. To examine the efficacy of their method, they construct another NFood-3d dataset using 42 food replicas with known portion size. However, for those artificial or real food items with dissimilar colour and texture property, the food segmentation fails and the volume of individual food item cannot be inferred, but estimated as a whole meal with error ranging from 50cm$^3$ to 400cm$^3$. Considering the number of food types in their meal used for evaluation, the average error for each food item ranges from 16cm$^3$ to 133cm$^3$. Similar idea has been proposed in [12] which aims at predicting Bread Units (BUs), a representation of food portion, for dietary assessment. In their work, CNN is also applied to infer the depth image using a single RGB image. Afterwards, the authors trained another network which follows the principal of Resnet-50 proposed in [13] by using both RGB images and ground-truth depth images (captured by Microsoft Kinect v2 sensor) as input. Instead of using a softmax layer, the last layer is replaced by a single neuron with $L_2$ cost function to predict the BUs. For this work, the performance of their proposed approach is evaluated using BUs so that it is not straightforward to compare it directly with other works. It is for this reason that we investigated into their depth prediction model to analyze the performance. As we know, the accuracy of volume estimation relies heavily on depth prediction. However, the depth prediction model proposed by [12] still achieves RMSE of 65cm in depth estimation, on the dataset of NYU Depth v2 and achieve 12.9cm, on their own food dataset. This error is considered to be reasonably small if it is used in mapping or robotic navigation but for the case of food volume estimation, this error is still unsatisfactory.

C. Deep Learning View Synthesis on 3D Models

From these previous findings, they showed that volume estimation by using depth prediction is inefficient due to the reason of inadequate information given in a single image to precisely reconstruct the 3D models, and insufficient representative training data to train the model, however, volume estimation based on deep learning is still worth investigating due to the reason of practicality and the ease of use. After a comprehensive exploration, we found that an integrated approach based on deep learning and 3D reconstruction could be one of the potential solutions in aiding dietary assessment. Specifically, deep learning view synthesis [14] can be used along with SLAM-based approach [6] to estimate the volume of food items without the need for the users to shift and rotate the camera to obtain the complete 360-degree view of the food. Although a number of research works, such as
PointNet [15] and PointNet++ [16], have explored the efficacy of using raw point cloud for classification, there are relatively fewer works using point cloud to perform view synthesis. In [9], the authors proposed an AutoEncoder (AE) architecture to tackle the problem of point cloud completion. Instead of directing the complete point cloud into the AE, partial point cloud is used as the input. Similar idea has been explored by [17]. Point completion network, an encoder-decoder network, was proposed to complete the point cloud with partial input. However, all these works are trained based on ShapeNet in which the models are scaled to a unit cube, losing the information about the portion size of the 3D models. Also, the partial and complete models are always aligned in canonical coordinates (8 directions), which means the network trained using this dataset is relatively difficult to complete partial point cloud captured in the wild (in any convenient viewing angle).

III. PROBLEM STATEMENT

The unsolved problems can be divided into different parts. First, it is necessary to explore an image capturing technique for dietary assessment without requiring users to take images from inconvenient viewing angles, such as from the back of the food items, and tackle the problem of scale ambiguity. Instead of using common 3D reconstruction approaches to scan the whole object items, it is preferable to scan the food items only from the front side. To complete the partial point cloud caused by the limited scanning angles, a point completion network is developed to complete the occluded part of the food items. Furthermore, most of the public datasets designed for view synthesis are normalized and centred to ease the image analysis, and which hinder portion size estimation. To address this problem, 3D models of 10 commonly seen food categories are constructed, tailored to examine the proposed point completion network in the wild.

IV. DETAILED INFORMATION AND METHODS

The pipeline of exploiting 3D view synthesis in dietary assessment can be divided into different steps. (1) A mobile phone with depth sensors or a ToF camera, such as Realsense or Kinect, is required to capture a single depth image or a video from any convenient viewing angle as shown in Fig.1A. (2) Food items for each frame are segmented out through a fine-tuned Mask R-CNN as shown in Fig.1B. (3) The depth image is converted from image to camera coordinate in order to obtain the partial point cloud for each food item as shown in Fig.1C. If a video is captured, a real-time 3D reconstruction technique, which has been proposed in [6], is used as an alternative choice to reconstruct the partial point cloud with more 3D information compared to that using a single depth image. (4) The partial point cloud is then directed to the point completion network to perform 3D reconstruction and estimate the portion size of the food items as shown in Fig.1D. (5) Once the food volume is estimated, the portion information can be linked to nutrient datasets, such as USDA, for detailed dietary analysis [18] as shown in Fig.1E. Note that this paper mainly focuses on food volume estimation using deep learning view synthesis so that the procedure of dietary analysis will not be covered.

A. Data Augmentation and Mesh Rendering

To examine the efficacy of the proposed volume estimation method using point cloud view synthesis, a large-scale 3D database is required. Instead of using the benchmark shape repositories like ShapeNet, which do not involve many food items and are normalized to fit within a unit cube, we used AutoCAD to build a new food dataset which consists of 10 commonly seen food categories including burger, fried rice, pizza, etc. Each category has 20 food models with different shape geometries and portion size. The scale of this dataset, however, is not big enough to train a completion network which can be applied in the wild. Leveraging the learning representations for 3D point clouds, a new data augmentation technique is applied to further enlarge the dataset. In [9], their findings showed that latent vectors, trained by a deep AutoEncoder (AE), enable shape manipulation easily. Linear interpolation has been used in the latent space among the same category to generate 4k food models (each category consists of 400 food models) with varying characteristics and portion size as shown in Fig.2. The equations for linear interpolation are shown in Equation 1 and 2.

\[ z_i = z_{A_1} + \frac{n}{d} (z_{A_1} - z_{B_n}) \]

where \(z_i\) is an element in a new latent vector, meaning \(i = 1, 2, ..., 128\), and \(d\) represents the number of fraction within the range of the initial vectors. By tuning \(n\), new latent vectors, which represent different shape geometries, can be generated through linear interpolation. The mathematical expression of the new generated latent vector can be written as Equation 2:

\[ z = [z_1 \ z_2 \ ... \ z_{128}] \]

After reconstructing new 3D models using the latent vectors, these models are annotated with their actual volume (\(cm^3\)) for portion size estimation as described in Section IV-B. Furthermore, to evaluate the ability of the point completion network in tackling the view occlusion problems in dietary assessment, another 3D dataset with occluded food items is constructed through mesh rendering based on the models generated from interpolation. In mesh rendering, the depth images of food items captured from various viewing angles are randomly generated, using the extrinsic camera parameter as shown in Table I, to simulate photo-taking events in the wild.

| TABLE I: The range of extrinsic parameters (azimuth, elevation, height and shifting) used in mesh rendering |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| **Azimuth** | **Elevation** | **Height** | **Shifting** |
|-----------------|-----------------|-------------|--------------|
| 0-360 degree | 325-345 degree | 0.70-0.90 m | x:0.1-0.1 m ; y:0.1-0.1 m |

After that, we transform the depth images from image to camera coordinate based on the intrinsic camera parameters (same as Intel RealSense) to obtain the partial point cloud of food items as shown in Equation 3.

\[
\begin{bmatrix}
    x \\
    y \\
    z
\end{bmatrix} = DK^{-1}
\begin{bmatrix}
    u \\
    v \\
    1
\end{bmatrix}
\quad \text{and} \quad K =
\begin{bmatrix}
    f_x & 0 & c_x \\
    0 & f_y & c_y \\
    0 & 0 & 1
\end{bmatrix}
\]
where \( u, v \) refer to the coordinates of the depth image and \( x, y \) and \( z \) refer to the coordinates of the camera coordinate, \( D \) is a scalar number which refers to \( depthimage(u, v) \) and \( K \in \mathbb{R}^{3x3} \) refers to the intrinsic matrix. Unlike ShapeNet, the point cloud constructed in this way is not centered and scaled to fit within a unit cube and which enables portion size determination. Before training the point completion network, several point cloud pre-processing techniques are carried out to facilitate the training of the network. (1) The point cloud is centered to the origin by subtracting the centroid of the point set, as shown in Equation 4.

\[
\text{centroid} = \left( \frac{\sum_{i=1}^{n} x_i}{n}, \frac{\sum_{i=1}^{n} y_i}{n}, \frac{\sum_{i=1}^{n} z_i}{n} \right) \quad (4)
\]

where \((x_i, y_i, z_i)\) represents the camera coordinate of data points \( i \) and \( n \) refers to the total number of points in the point set. This alignment enables the point completion network to tackle food items placed in any position without requiring the food items to be placed in the center of the image. (2) The point cloud is then down-sampled through a voxel grid filter which takes a spatial average of the data points in every single voxel. (3) Statistical outlier removal filter is applied to remove the outliers from the point set to alleviate the effects of environmental noise. To remove the outliers, we first compute the average distance to \( k \) nearest neighbors distances \( (knn) \) for each point. Then, the point with average distance larger than \( n \) standard deviation of the average distance across the point cloud is marked as outlier and removed as shown in Equation 5.

\[
f(p_i) = \begin{cases} 
\text{outlier} & \text{if } d(p_i) > n \text{(S.D.)} \\
\text{inlier} & \text{if } d(p_i) \leq n \text{(S.D.)} 
\end{cases} \quad (5)
\]

where \( d(p_i) \) refers to average distance to \( k \) nearest neighbors for \( p_i \) and \( S.D. \) represents the standard deviation of the \( d(p_i) \) across the point cloud. Note that \( n, k \) and voxel size are determined empirically in this paper.

**B. Volume annotation**

To annotate the generated models with their corresponding volume, we calculate the bounding polygon of the models with the alpha-shape algorithm [19], [20]. By using alpha-shape algorithm, a sphere with a fixed radius is firstly defined. Afterwards, the sphere is rotated with its circumference around the models from a chosen starting point until the sphere touches another point lying on the contour. The sphere is transferred to this point and the process continues until reaching loop closure. In Figure 3, the complete point cloud of a 3D banana model is converted into a 3D mesh using the alpha-shape algorithm. Once the 3D mesh is obtained, the volume of the 3D models can be deduced easily. Afterwards, all the paired point cloud and its corresponding volume information will be used to construct the training dataset for training the volume estimation network. One more step is required before using this volume information of 3D generated models to estimate the actual volume of the original food items. Since the partial point cloud is captured using a depth camera, point-to-point distance should be carefully calibrated which represents a specific distance in the real world. A real Rubik’s cube with known volume \( (343 \text{cm}^3) \) is used as a scale reference for calibration in this work. Similar calibration method has also been proposed in [6]. When the point cloud is completed using the point completion network to form generated 3D models,
the volume of these generated models can be estimated. By considering the scale difference between the generated 3D models and the original food items, the volume of the generated 3D models can be converted to the actual volume of the food items using the calibrated scale/value.

C. Point Completion Network

Due to the problem of view occlusion by taking photos from limited viewing angles, only the 3D points from one side of the food items can be observed. If using partial point cloud to determine the portion size, the volume of the food items will be largely underestimated. To address this problem, a novel point completion network UNet, shown in Fig.4B, is built on top of recent encoder-decoder architectures, tailored to predict the occluded 3D points using the partial input [9]. In the proposed architecture, the partial point cloud with 2048 points (2048 x 3 matrix) is directed into a feature encoder, which consists of several shared multilayer perception (MLP) layers. Through these multilayer perception layers, each data point \( p_i \) is converted into a point-wise feature vector \( v_i \). Since the order of the point set will affect the training of the network, it is necessary to make the point set permutation invariant which indicates that the order of the point set does not change the geometry they represent. To achieve this, the architecture follows the design of the PointNet [15] which applies a max pooling layer after the MLP to squeeze the feature vectors into a single representation known as a latent vector. For the decoder, several network architectures are compared, including fully connected [9] and UNet architectures, to evaluate the generalization ability in predicting hold-out object items. For FC architecture, it is considered as a lightweight implementation of the point completion network. After passing through the latent vector, it is followed by several FC layers, as shown in Fig.4A, to generate the geometrical representation of the complete 3D models. Regarding to the similarity between partial and complete point clouds, we hypothesize that the point-wise features near the partial input can provide significant guidance in predicting the complete point cloud. In UNet architecture, instead of using pure FC layers, point-wise features are concatenated to these FC layers after passing through max-pooling layers respectively as shown in Fig.4B. Apart from this, the symmetric version of Chamfer Distance (CD) inspired by [17], [14], as shown in Equation 6, is used as the cost function of the point completion networks. In using symmetric CD, penalty will be induced to the cost function if the partial and complete point cloud are not on the same scale. This facilitates scale determination as well as volume estimation.

\[
CD(G, C) = \frac{1}{|G|} \sum_{g \in G} \min_{c \in C} \|g - c\|_2 + \frac{1}{|C|} \sum_{c \in C} \min_{g \in G} \|c - g\|_2
\]  

where \( G \) and \( C \) refer to the ground truth and complete point cloud respectively, \( g \) and \( c \) represent each point in the point cloud.

D. VolumeNet (VNet)

To estimate the portion size, the common approach is to carry out alpha-shape algorithm. While the performance of alpha-shape algorithm shows promising results, there still exist several procedures which complicate the process such as the radius of the sphere should be determined empirically as mentioned in Section IV-B, and the estimation error is easily induced when the points are not evenly distributed. Specifically, the real number \( \alpha \) refers that the meshed model is constructed by a set of edges and triangles with radii not over \( 1/\alpha \), which relies heavily on the sampling rate and the geometries of the meshed models. Thus, \( \alpha \) is always
determined empirically by a user (calibration). To facilitate
the dietary assessment and enable automatic quantification, an
alternative approach, VNet, as shown in Fig. 4 is also proposed
in this work to estimate the portion size without requiring the
use of alpha-shape algorithms. To the best of our knowledge,
this is the first work on using deep learning to estimate object
volume directly by taking raw point cloud as input. The
network for volume estimation is similar to the architecture
of the point completion network. The feature encoder of VNet
follows the design principle of completion network which also
takes raw point cloud as input. By using shared MLP and
max-pooling layers, we can also ensure the network to be
permutation invariant. However, the complete point cloud is
directed into the network instead of the partial one. After the
latent vector, three FC layers are followed to infer the actual
food volume (cm$^3$). In this case, a simple L1-norm is used as
the cost function as shown in Equation 7.

$$\text{Cost} = |V_{\text{estimated}} - V_{\text{groundtruth}}| \quad (7)$$

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. Performance of point completion network in handling view
occlusion

To examine the efficacy of the point completion networks,
various experiments have been carried out which aim to
evaluate the generalization capability of the point completion
networks in handling different scenarios. To construct the
training dataset, $2.4k$ 3D models (generated through linear
interpolation) from 8 food categories, including banana, apple,
burger, cake, pizza, orange, rice and donuts, are used. For each
3D model, 20 partial inputs from different viewing angles are
generated through mesh rendering using the range of extrinsic
camera parameters as shown in Table I. The networks are then
trained end-to-end by using 3D models from these categories
with 48k partial inputs in total. For testing, 3D food models
with unknown geometries, portion size and viewing angles
are directed into the neural network to simulate the real-
world photo capturing. Specifically, 800 hold-out models from
previously seen categories ($16k$ partial inputs) and 200 models
from another 2 novel categories ($4k$ partial inputs) are used to
evaluate the generalization capability of the networks in
tackling food items with previously unseen viewing angles
and geometries respectively. Note that all the networks are
trained using Adam optimizer for 750 epochs with the batch
size of 100. In Fig. 5, the qualitative results of the point
completion networks based on deep learning view synthesis
are presented. Partial hold-out food items chosen from 8
known categories and 2 new categories captured from different
viewing angles and positions are processed using the FC and
UNet architectures respectively, which provide the evidence
that point completion networks are capable of addressing the
problem of view occlusion. In previously seen categories,
the performance in both of the FC and UNet architectures
is comparable; however, we found that the extended UNet
has a better generalization ability in predicting new categories
(hotdog and muffin). A similar conclusion can also be drawn
in the quantitative results as shown in Table II. Although the
training loss measured by Chamfer distance shows promise
in FC architecture, the performance of UNet outperforms FC
architecture in testing which indicates that FC architecture is
easier to cause over-fitting.

B. Performance of food volume estimation using deep learning
view synthesis

The feasibility of using deep learning view synthesis to
estimate the actual portion sizes of food items is also eval-
uated. This experiment is carried out on top of the point cloud
completion. Once the partial point clouds are completed, they
are converted to 3D mesh by the alpha-shape algorithm and
the food volume is then computed. As shown in Table II, the
experimental results of food volume estimation using UNet
is promising with average training and testing accuracy up to
95.16% and 92.29% respectively. The system is also robust
with only 5.12% in averaged standard deviation (S.D.) for
the testing dataset. Furthermore, the accuracy for individual
food category is listed out in Table II. It is shown that the
categories of cake and muffin have significant improvement in
volume estimation by using UNet compared to FC architec-
ture. While the cake belongs to the seen category, the volume
accuracy drops sharply when FC architecture is applied. After
comprehensive exploration, we found that the main reason
for this is due to the large variance between the training and
testing datasets for the cake models so that some of them are
treated as unseen objects by the FC network. Nevertheless,
the UNet architecture is generic enough to tackle the problem
without over-fitting and predict the complete models with
promising accuracy. Again, these results prove our hypoth-
thesis that point-wise feature vectors can provide guidance in
completing unseen shape geometries and provide the network
with better generalization ability. Most importantly, all these
findings conclude that point completion networks can be used
to estimate the food volume with unknown geometries, portion
size and viewing angles which in turn makes our proposed
method effective in quantifying the portion size consumed by
the users.
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TABLE II: Quantitative results of the FC and UNet architectures in deep learning view synthesis and volume estimation

| Food Object | Training Loss (CD) | Testing Loss (CD) | Training Accuracy(%) in Volume | S.D. (%) | Testing Loss (CD) | Testing Accuracy(%) in Volume | S.D. (%) |
|-------------|-------------------|------------------|-----------------------------|----------|------------------|-----------------------------|----------|
| Banana      | 0.15              | 0.15             | -                           | 91.10    | 16.10            | 0.19                        | 94.25    |
| Apple       | 0.11              | 0.29             | -                           | 93.11    | 8.64             | 0.18                        | 95.61    |
| Burger      | 0.72              | 0.76             | -                           | 97.91    | 2.76             | 0.71                        | 96.49    |
| Cake        | 0.15              | 0.73             | -                           | 89.47    | 11.05            | 0.21                        | 96.14    |
| Pizza       | 0.13              | 0.26             | -                           | 92.21    | 3.32             | 0.19                        | 91.18    |
| Orange      | 0.09              | 0.18             | -                           | 97.38    | 2.10             | 0.18                        | 95.27    |
| Rice        | 0.06              | 1.31             | -                           | 94.07    | 2.36             | 1.37                        | 94.91    |
| Donuts      | 0.11              | 0.21             | -                           | 95.58    | 5.21             | 0.18                        | 93.32    |
| Hotdog      | -                 | 2.32             | -                           | 79.17    | 12.67            | 1.75                        | 80.35    |
| Muffin      | -                 | 2.46             | -                           | 74.55    | 10.64            | 2.10                        | 85.34    |
| Average     | 0.15              | 0.26             | -                           | 97.68    | 7.49             | 0.40                        | 95.16    |

*Training loss and training accuracy are calculated based on the training dataset with 3 categories, each category contains 100 models and each model has 20 different viewing angles (40k partial inputs in total). Testing loss and testing accuracy are calculated based on the testing dataset with 10 categories, each category contains 100 models and each model has 20 different viewing angles (20k partial inputs in total).

C. Efficacy of VNet in volume estimation

The performance of VNet is evaluated by comparing its results with the results estimated by alpha-shape algorithm. Similar to the previous experiment, hold-out food models are used to examine the trained VNet to ensure the fairness and test its robustness. Thus, the complete point cloud of food items from 8 categories with 16k models completed by UNet are used in this experiment. The average testing accuracy in volume estimation for VNet can achieve up to 82.90%. Considering the light-weight implementation, the VNet got a reasonable drop with error rate in only 12.40% compared to the result estimated by traditional alpha-shape algorithm. Comparison of volume estimation using both of the methods for each category is also shown in Fig.6. Despite the performance of VNet dropping slightly compared to the alpha-shape approach at the current stage, the VNet is a generic feed forward neural network approach which is more efficient and easier to use. Furthermore, the performance of data augmentation, which refers to linear interpolation here, is also evaluated in this experiment. Another training dataset is built by eliminating 3D food models generated by linear interpolation of latent space and VNet is trained using this newly constructed dataset. The comparison of the performance of VNet trained by datasets with data augmentation and without data augmentation is shown in Table III. This illustrates that the proposed data augmentation technique significantly facilitate the training of VNet and help better estimate the volume. Furthermore, it also means that the accuracy of volume estimation relies heavily on the size of the training dataset. From these findings, we hypothesis that the accuracy of VNet can be further improved when more 3D models are generated using linear interpolation.

D. Point cloud completion in the wild

To further evaluate the robustness of our proposed dietary assessment method, experiments are carried out in the real world scenarios. Instead of using synthetic dataset, the trained point completion network is evaluated using images of real food items. An experimental platform is set up in a photo studio as shown in Fig.7 to obtain the ground truth volume of food items by dense 3D reconstruction. The food items are placed on an automatic turning table which keeps rotating while the depth camera is recording. The 3D models of real food items are constructed and the ground truth volume can then be obtained using RecFusion, a professional 3D scanning system which performs dense 3D reconstruction and volume estimation. After the ground truth is obtained, the experiment of point cloud completion is carried out. First, videos (6 trials for each food item) are captured from convenient viewing angles (only from the front side). 3D reconstruction is then applied to reconstruct the partial point cloud as the input of UNet. The qualitative results of using UNet to handle the problem of vision-occlusion are shown in Fig.8 which present the meshed partial inputs using 3D reconstruction, meshes of food items completed by UNet and the ground truth. Further experiments are carried out to examine the performance of the proposed technique in comparison with the method based on 3D reconstruction only. As shown in Table IV, the experimental results of food volume estimation using both real-time 3D reconstruction and UNet in the wild are promising with mean accuracy up to 84.68%. In the table, it also indicates that the proposed method can effectively address the problem of view occlusion due to limited viewing angles and ease the implementation of vision-based dietary assessment system.

VI. DISCUSSIONS

A. Comparison with related works

The existing research studies on food volume estimation have only examined their algorithms on self-constructed testing datasets with several food items captured in the wild in which there does not exist a benchmark that allows researchers...
Regarding previous deep learning approaches [11], [12], they rely heavily on depth prediction markers in the view. Regarding previous deep learning markers near the food items and take photos/videos with the lead to user compliance issues as the user has to place the facilitate the feature matching between frames, which could approach requires a fiducial marker to determine the scale and objects. Furthermore, traditional multi-view 3D reconstruction since the previous method can only handle symmetrical food partial point cloud of the food items. Compared to [6], our pro-

completion network addresses this problem by completing the of images and their capturing positions. However, our point [23], they usually have strong requirements on the number approaches [22], to conduct a fair comparison with previous approaches. Thus, it is reasonable to evaluate our proposed algorithm from the perspective of practicality and implementation. For the to recognize the partially eaten food items and estimate remaining

direction in tackling the food volume estimation problem.

VII. FUTURE WORKS

The proposed technique was initially designed to help dietitians record down the entire portion of food items shown in the meal times. Users are expected to capture the images/videos at the beginning of the meal time for recording the full meal. For the scenarios where the food items are just partially eaten, this paper has not yet covered and discussed. In addition, to estimate the exact portion size taken, the algorithm should be able to calculate the remaining food volume after the meal. It is for this reason that a more advanced system could be developed which consists of newly trained neural networks to recognise the partially eaten food items and estimate remaining food volume in real-time.

VIII. CONCLUSION

A novel dietary assessment method based on real-time 3D reconstruction and deep learning view synthesis is presented to estimate food volume in this paper. The developed approach shows the feasibility and efficiency in portion size estimation under the circumstances of occluded views. By using the proposed point completion network UNet, the point cloud of the occluded food items can be completed using the prior learned shape and the food volume can be estimated with accuracy up to 92.29%, which not only outperforms other deep learning based approach but also addresses several key challenges in the field of dietary assessment.

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### TABLE III: The comparison of the performance of VNet trained by datasets with and without data augmentation (generated through linear interpolation)

| VNet (-Augmentation) | VNet (+Augmentation) |
|----------------------|----------------------|
| Average Accuracy (%) | Average Accuracy (%) |
| Banana 62.46±23.01 | Orange 90.74±6.93 |
| Apple 60.14±46.81 | Burger 93.31±28.72 |
| Burger 64.48±24.43 | Cake 83.59±21.31 |
| Cake 81.91±15.45 | Pizza 87.12±10.11 |
| Pizza 49.16±11.62 | Orange 77.83±9.40 |
| Orange 72.33±22.64 | Rice 82.59±10.83 |
| Rice 60.19±11.22 | Donuts 72.36±12.73 |
| Donuts 78.28±15.01 | Average 82.90 |

### TABLE IV: Quantitative results of food volume estimation using 3D reconstruction with and without UNet

| Food Object | Ground Truth (cm³) | Mean Estimated Volume (cm³) | Accuracy (%) | Mean Estimated Volume (cm³) | Accuracy (%) |
|-------------|---------------------|----------------------------|--------------|----------------------------|--------------|
| Banana      | 130.34              | 93.82±7.34                | 71.67        | 114.23±12.57              | 87.64        |
| Apple       | 248.53              | 136.76±9.81               | 55.03        | 220.21±5.24               | 88.60        |
| Burger      | 421.11              | 391.34±17.30              | 92.93        | 436.26±13.92              | 96.40        |
| Cake        | 350.57              | 244.35±13.43              | 69.70        | 320.23±14.23              | 91.34        |
| Pizza       | 109.24              | 90.12±6.43                | 82.50        | 88.56±10.14               | 81.10        |
| Orange      | 298.34              | 167.75±10.36              | 56.22        | 243.95±8.53               | 81.77        |
| Donuts      | 351.47              | 230.53±11.56              | 65.59        | 279.10±12.47              | 79.41        |
| Hamburger   | 390.86              | 280.59±21.90              | 71.78        | 446.69±17.31              | 85.72        |
| Muffin      | 206.17              | 161.35±17.52              | 78.26        | 232.71±11.25              | 87.13        |
| Baguette    | 377.31              | 294.51±22.32              | 78.10        | 456.22±15.33              | 79.08        |
| White Bread | 173.81              | 113.39±23.15              | 65.24        | 220.15±13.64              | 73.33        |
| Average     | -                   | 71.54                     | -            | 84.68                     |              |

Fig. 7: The experimental platform for obtaining the ground truth volume of food items in the wild.

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Fig. 8: Examples of using UNet for point cloud completion and 3D meshing in the wild

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