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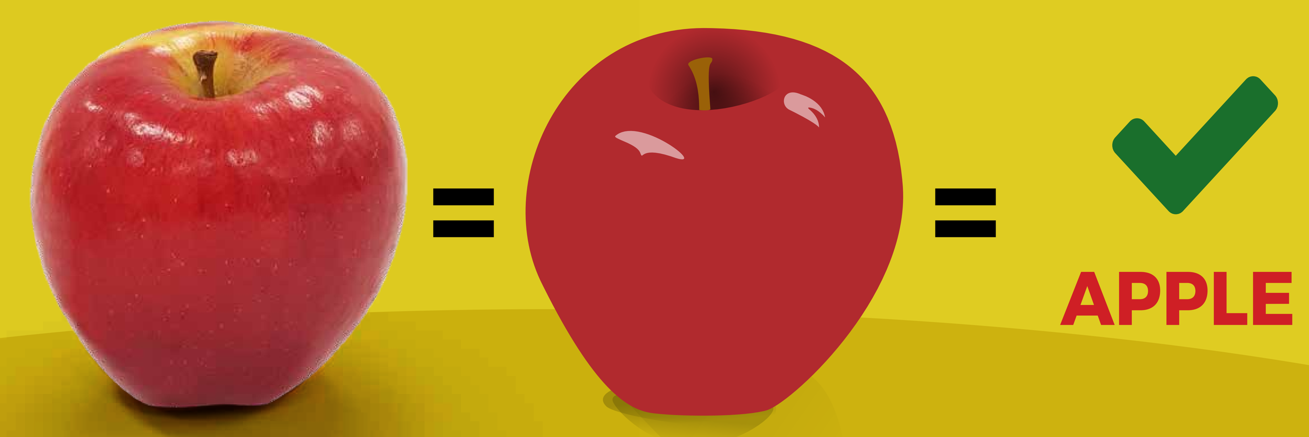
Automated Meal Compliance

Using Deep Learning Techniques for Individualised Hospital Catering – Pilot Study



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Background

A wide variety of food service systems exist for the provision of food in hospitals. Most food service systems are labour intensive and rely on staff training and staff attention to ensure meal compliance. Meal compliance is particularly important in the hospital setting where vulnerable patients receive specialised diets to meet their nutritional requirements. Diets in hospital consider patient food preferences as well as delivering therapeutic needs which includes consideration to allergens and food intolerances. Accurate analysis of food and recording details of food provision against individual patients has gained considerable attention due to the importance of food to human health, especially in the hospital system. There are many important factors which contribute to a quality food service system and these include accuracy, appearance, temperature, texture, and taste of meals [1]. Food safety is also a major part of any food services system. Potential issues include provision of food containing allergens or contamination. These can lead to adverse effects of physical health and can be fatal in severe cases. It is also important to provide the correct type and quantity of food to the patients to ensure they are meeting their nutritional requirements. Failure to provide adequate nutrition may lead to malnutrition and complications which may cause increased length of hospital stay and greater in hospital mortality [2]. Providing meals without human errors, and ensuring all foods are safe and are good quality is a big challenge for most organisations. Recently, use of deep learning (DL) has demonstrated successful real-life applications in image recognition in other industries and there is a potential to apply these technologies in hospital kitchens. The Canberra Hospital (TCH) is aiming to develop an automatic system that is able to monitor the food intake of patients [3].

Aim

To explore the use of DL on the applicability of meal component recognition to improve meal compliance in an acute care hospital facility.

Method

Deep Learning (DL) is a branch of artificial intelligence that is capable of recognising images automatically. There are a number of successful DL applications in image recognition. In the automotive domain, self-driving cars collect images through their camera sensors. DL is then used to identify and analyse the images collected by these sensors. When a self-driving car recognizes a red light ahead, it will activate the automatic brake function [4,8]. Another application of DL is to automatically recognise car plate characters for intelligent traffic management purpose [5]. For our application, rather than recognising the traffic light or plate characters, we collect food component images, from meal trays from The Canberra Hospital (TCH) kitchen, for meal compliance purposes. Convolutional Neural Network (CNN) is leading DL in image analysis at present (Figure 1). It mathematically expresses an image into a combination of different fully connected (FC) layers for identification and classification. Each image is transformed into a multi-dimensional matrix through a computational process. A DL model is applied to measure the similarity of these images through extracting the attributes represented by the matrices from the input images [6]. In TCH kitchen, 2 cameras facing the meal tray in 2 different angles take two different photos of the tray (Figure 3). A prototype system with a DL model has been implemented. To date, we have obtained 2400 food component images from 16 different categories. We applied two different CNN models, which are Visual Geometry Group (VGG) and Resnet to the images. Since each of these 2 models require a large number of parameters to train the models, a massive dataset is required [6]. Transfer learning is then applied to alleviate the problem. Figure 2 displays the framework of transfer learning being applied to the 2 pre-trained models, VGG11 and Resnet18, to build the models from the images collected.

Fig. 1. Example of food image in CNN process

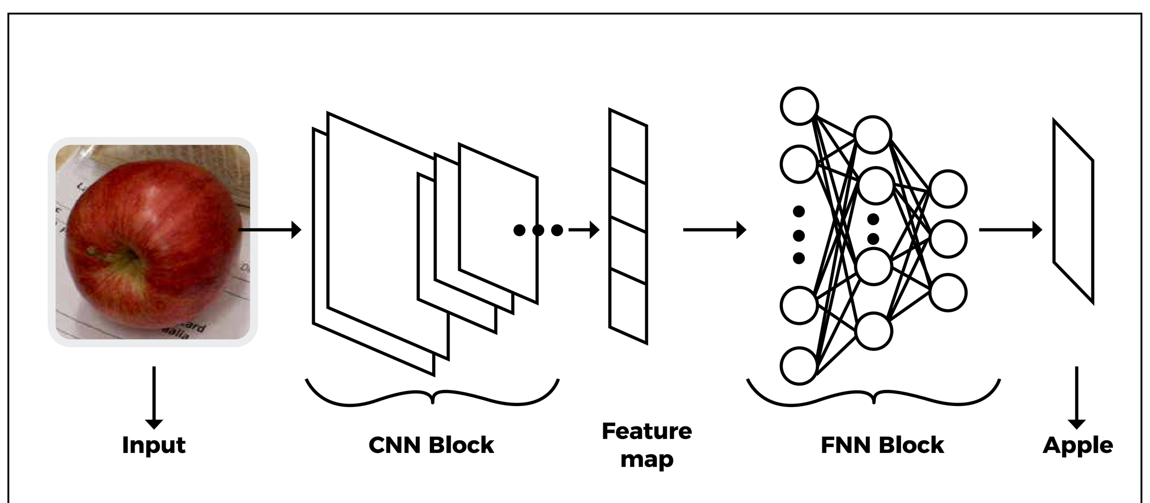


Fig. 2. The framework of transfer learning applied to pre-trained model to build a model with new dataset.

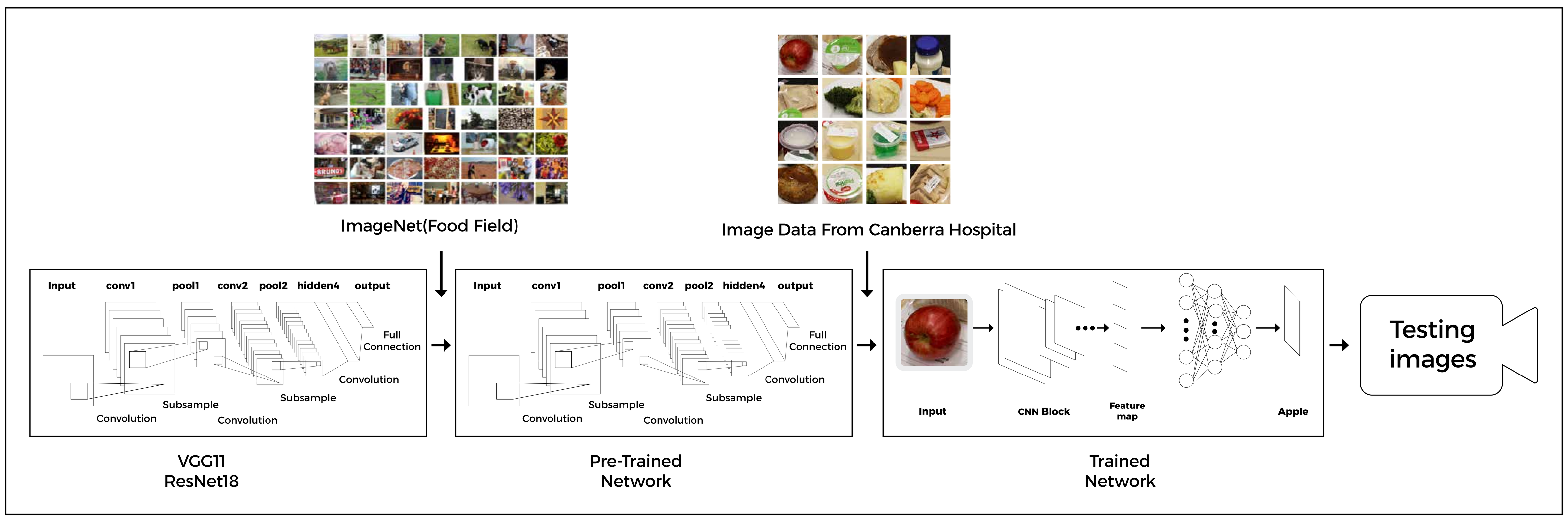
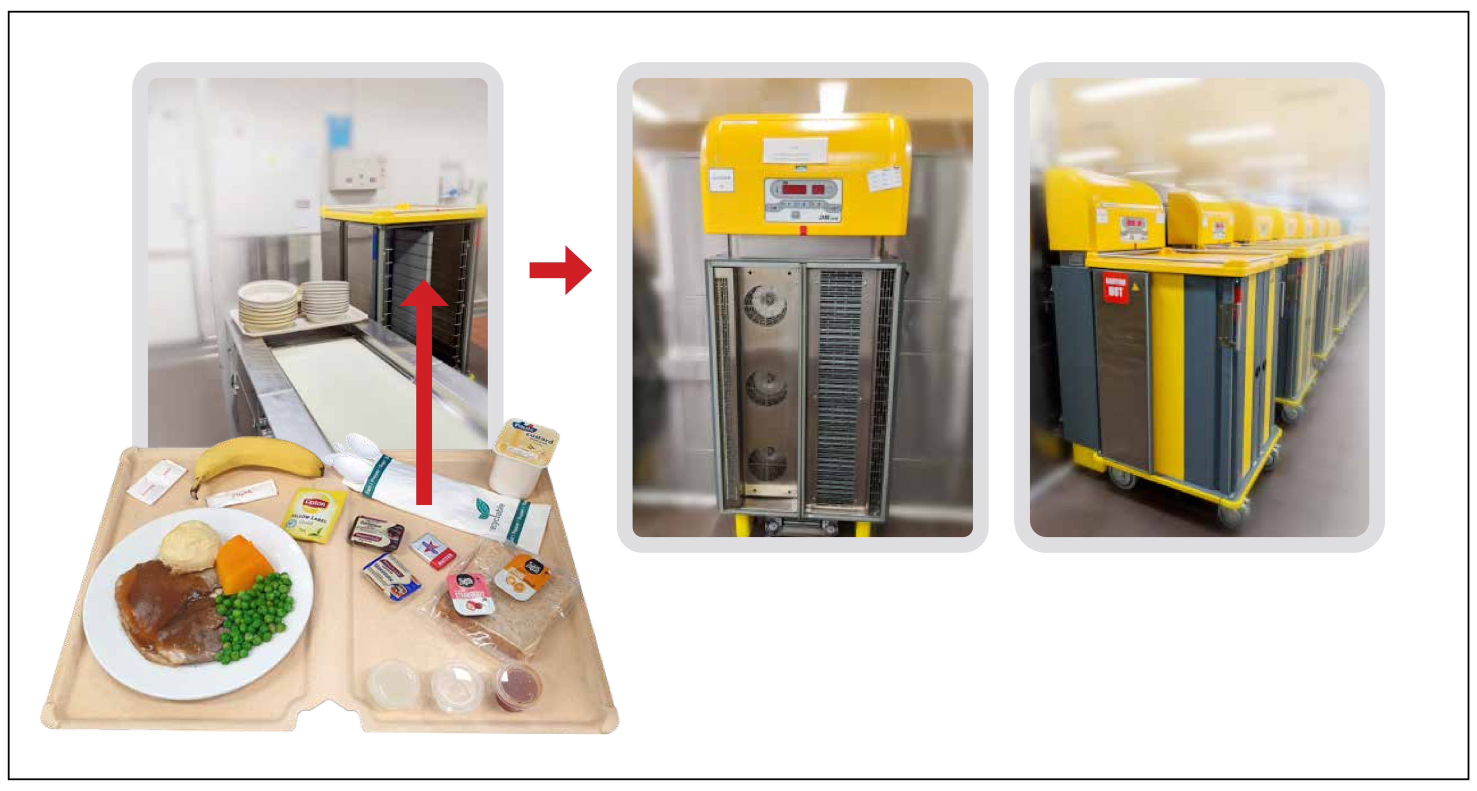
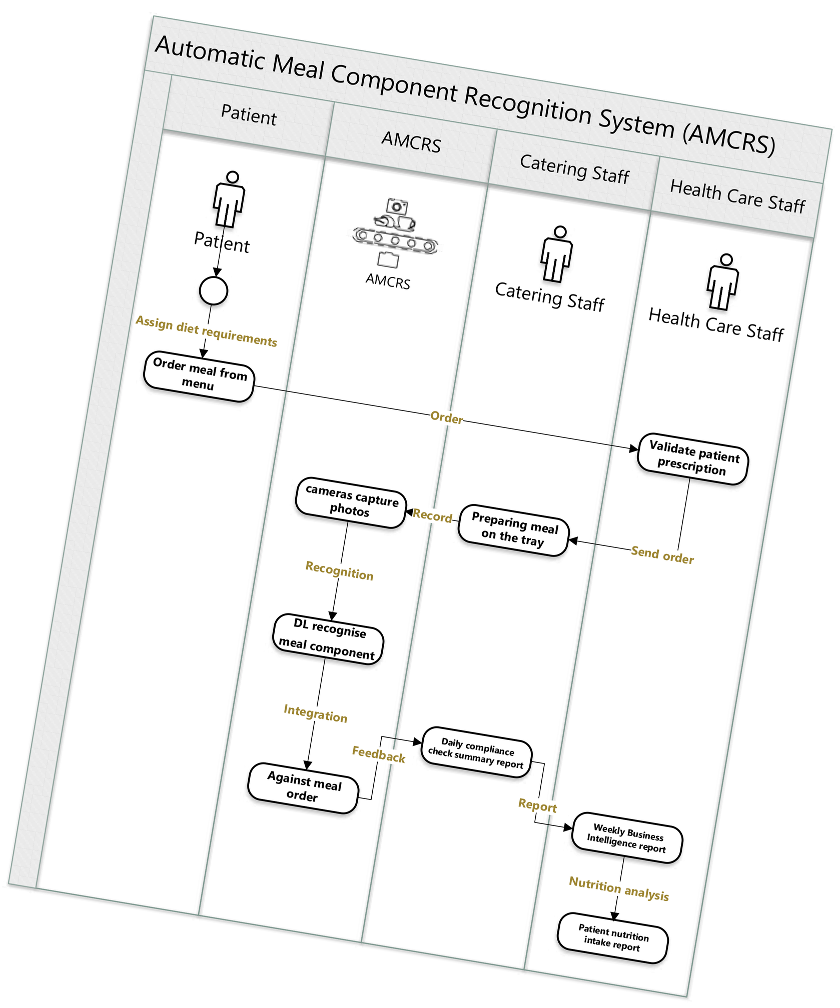


Fig. 3. Demonstration of TCH kitchen





Results

The collected image datasets were from meal trays consisting of a meal (2 choices) and meal components (16 component choices). For each component category, 150 digital images were collected, these images are divided into training (n=90 images), validation (n=30) and testing (n=30). The training and validation results of both VGG and Resnet-18 models provided recognition accuracy higher than 90%.

Conclusion

The use of a DL image recognition system has the potential to offer a safer food service quality control in the hospital setting. This research project highlights the potential of new technologies such as advanced artificial intelligence, and DL, in the management of large food service systems. The findings provide a stepping stone towards the more accurate and less labour intensive serving of meals to highly vulnerable populations such as patients in hospitals.

References

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