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Nutrition-rich Food Suggestion for Cancer Patient using CapsNet

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Abstract: Food is important for human survival and has been the focus of several medical conventions. Novel dietary assessment and nutrition investigation technologies now provide more options to assist people in understanding their regular eating habits, researching nutrition trends, and maintaining a balanced diet. People with cancer are now advised to eat a nutritious, balanced diet in order to maintain their quality of life and achieve optimal health results. It is necessary to maintain a healthy body weight and to consume nutritional foods. The major purpose of this work is to provide healthy and nutritious meal suggestions for cancer patients. This research proposes a CapsNet model, a kind of deep neural network, for food recommendation. Preprocessing, feature extraction, and classification are the three key procedures in the proposed study. Reshaping, squash function and routing agreement are the major operations of the proposed work. There are six layers are used to build the CapsNet model which also has the two main layers called Primary Capsule layer and Food Capsule layer. After preprocessing of the food image, the features are extracted. As a final point, depending on the identification outcomes, the system will evaluate the nutritional substances and afford a dietary assessment report by estimating the capacity of fat, calories and carbohydrate. For analysis Food-101 dataset and cancer patient dataset are used. The performance of the proposed methodology is analyzed through different evaluation metrics and achieving an accuracy of 95% and the loss value also decreased. To prove the effectiveness of the proposed methods, this study presents a comparison with the advanced techniques.

Keywords: *CapsNet, Deep Neural Network, Food Capsule layer, Primary Capsule layer, Routing Agreement*

1. Introduction

Cancer therapies are intended to eliminate cancer cells. However, these therapies can potentially harm healthy cells. Damage to healthy cells might result in adverse effects that result in eating difficulties. Nutrition is an important part of cancer treatment. Eating the correct meals can help you feel healthier and stay stronger before, during, and after therapy. Cancer patients' nutritional requirements differ from one another. A healthy and nutritional diet plays a massive role in preventing illnesses like cancer among people, especially recovering patients. However, in most situations, people struggle to estimate and measure their food consumption due to inadequate of nutritional knowledge [1].

The purpose of a diet plan is to ensure that the cancer patient improves their food intake. This will reduce the risk of interruptions in their scheduled anti-cancer treatment, thereby improving the treatment outcomes and their overall quality of life. It is necessary to consider both the good and bad nutrition while analyzing nutrition in food, but most of the existing works did not consider these types and few of them have just assumed some nutrients as good or bad.

The good and bad nutrients differed according to the patient health. So, it is necessary to identify the good and bad nutrients in the food accurately which determines the patients' strength. For effectively classifying the food and suggest a good plan, in this work CapsNet based food recommendation system is proposed. This model classifies the food as per the patient data and it overcomes the accuracy problem which is happened in the existing work.

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The contributions of this work are summarized as follows:

- To improve the classification accuracy, number of convolutional layers are used in this work. It automatically extracts high number of specific features from the image. These number of features makes the classification process easier and more accurate.
- To reduce the loss of the model CapsNet model is considered. The issue of losing certain spatial connectivity among the links is resolved because CapsNet saved all of the mined local attributes by simply changing the pooling approach by a dynamic routing procedure among the capsules.

The rest of the work is organized as follow. Section 2 presents literature survey about food recommendation system using various techniques and CapsNet model. Section 3 contains the methodology of the proposed work. Section 4 has performance evaluation which shows the efficiency of the proposed work. Section 5 contains conclusion and future work of our proposed study.

2. Literature Survey

Gao *et al.* (2020) created a specialized neural network approach Hierarchical Attention-based Food Recommendation (HAFR) is responsible of: 1) collecting the collaborative filtering effect, such as what comparable users tend to consume; 2) assessing a user's choice at the ingredient level; and 3) understanding user selection from the visual pictures of the recipe. Despite obtaining cutting-edge meal recommendation performance, the work has several limits. Because this work does not include healthy and nutrition components, it cannot guarantee the health of the suggested recipes.

Rostami *et al.* (2022) created a new hybrid food recommender method to address prior systems' weaknesses, such as neglecting food components, time factor, cold start users, cold start food products, and community elements. The suggested technique is divided into two stages: food content and user-based recommendations. In the first step, graph clustering is employed, and in the next, a deep learning based technique is used to cluster both individuals and food products. A comprehensive method is also used to account for time and user-community difficulties, which increases the quality of the suggestion supplied to the user. This work does not consider the nutritional characteristics of each food and person's health status and diseases.

Kalyani *et al*. (2021) devised a capsule network for detecting and classifying diabetic retinopathy. The features from the fundus pictures are retrieved using the convolution and primary capsule layers, and the likelihood that the image belongs to a particular category is evaluated using the class capsule and Softmax layer. Feature extraction was done by first two layers, whereas the class capsule layer is utilized to determine the probability of a specific class.

Naik (2020) suggested a recommendation method that is trained based on the suggestions of previous customers who have utilized the product. The software offers the product to the customer based on the consumer's prior experience with the same product. Each person has his or her unique eating habits depending on the user's wishes and dislikes, implying that a tailored diet is necessary to maintain the user's progress and health. To deliver the best recommendations, the suggested recommendation approach employs a deep learning algorithm and a genetic algorithm.

Shanthi & Rajkumar (2020) suggested a wrapper-based feature selection approach based on the modified Stochastic Diffusion Search (SDS) algorithm. In order to discover appropriate feature subsets, the SDS would benefit from direct agent contact. For classification, neural networks, Nave Bayes, and decision trees were utilized.

Shanthi & Rajkumar (2019) suggested a symbolic method to data analysis that makes use of a wide range of quantitative data. The research also looks at several feature selections approaches for predicting the histologic subtypes of lung cancer using either symbolic data or radiomic characteristics. These features were retrieved using a gray-level co-occurrence matrix (GLCM), the Gabor filter, and fusion accomplished by concatenation after the Z score was normalized.

3. Methodology

A novel deep neural network architecture is used in this proposed work to offer highly nutritious meals to cancer patients based on their health information. This work has three major steps such as preprocessing, feature extraction and classification. Totally six layers are implemented in this proposed work, first three layers are works under the feature extraction phase, remaining three layers works under the classification phase. The detailed explanation and working process of each layer are provided in the upcoming sections. The overall architecture of the proposed work is shown score was normalized.

3.1. Dataset

3.1.1 Food Dataset: This suggested model takes use of the meal dataset, which has 101 food [6] types and 101'000 photos. 250 manually approved test photos and 750 training pictures are offered for each class. The training photos were not cleared on purpose, so they still include some noise. This manifests itself mostly through bright shades and, on occasion, incorrect labelling. Every image was resized to have a maximum length of 512 pixels.

3.1.2 Cancer Patients Dataset: Patient datasets differ depending on the patient's bodily state and cancer stage, such as early, medium and severe. The food dataset is utilized for categorization and develops score was normalized.

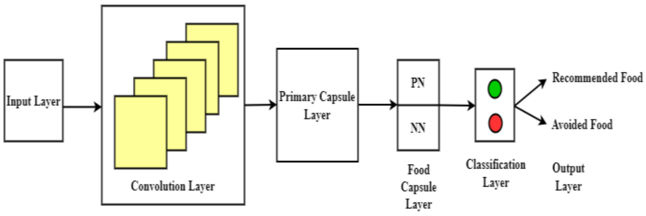

Fig 1. Architecture of the proposed work.

3.2. Preprocessing

The suggested work's initial stage is preprocessing. The classification model's accuracy or quality is determined by the quality of the input utilized for training phase. As a result, the training data in the datasets are preprocessed before being considered as inputs. Preprocessing is the process of formatting pictures before they are utilized in model training and validation. The food photos in the databases vary in size. As a preliminary stage in preprocessing, all photos are scaled to 512×512 pixels in size. The noise in the photos is eliminated using Gaussian filtering in the second stage. The input photos are transformed to equal sizes and the noise is reduced as a consequence of the two-step preprocessing.

3.3. Feature Extraction

The second stage of the proposed work is feature extraction which plays a vital role in the whole process. The final output was fully depended upon the feature extraction process. Three layers are used in the feature extraction phase to extract the most essential features from the food images. The three layers are input layer, step preprocessing.

3.3.1 Input Layer

The initial layer of the proposed capsule network is an input layer, where inputs are supplied into the network. There were two main types of inputs utilized. They are as follows:

- Cancer patient health details
- Food images

This input layer receives both the food image dataset and a dataset preprocessing.

3.3.2 Convolution Layer

This is the suggested capsule network's second layer. This layer conducts a "convolution" action. A convolution, like a standard neural network, is a linear process that includes the multiplication of a set of weights with the input food picture. Because that the approach was created for two-dimensional input, the multiplication is conducted among an array of input food images and a two-dimensional array of weights known as a filter or a kernel.

The choice of a filter lower than the input is deliberate since it lets the same filter to be multiplied by input array several times at diverse locations on the input. This continuous use of the same filter over an image is a powerful idea. Whether the filter is developed to detect a particular feature in the incoming meal image, then using that filter constantly throughout the whole meal photo permits the filter to recognize that feature wherever it appears in the image. This is referred to as translation invariance.

This layer accepts input data that is food image and patient details from the previous layer and extracts features from the food images. It extracts the features like ingredients, colors, texture etc. These preprocessing.

3.3.3 Primary Capsule Layer

Third layer of the suggested work is primary capsule layer. The extracted food image's feature map is given as input to the primary capsule layer. Here the extracted features positional information, presented nutrients and probability of the nutrients are predicted. The primary capsule layer changes the low-level scalar feature depictions into high-order vectorial capsule representations. It of two distinct processes: Reshaping and Squash function.

a. Reshaping

Now, use the Reshaping method to reformat the feature maps of the food photos into vector format. At example, for each position in the food picture, it is reshaped into four vectors of 9 dimensions each ($36 = 4 \times 9$). The vector form of the food images contains the ingredients positional information, location, direction information, nutrients of the food. The main advantage of representing the images is in vector form is identifying the position and direction of the object. With the help of these information the model can able to identify the object in the images in any form like rotated in any angle. Finally, the reshaping function prepares the data for the squash operation before it is passed to the food capsule layer.

b. Squash Function

Its last stage of the primary capsule layer is to ensure that the length of every vector is less than one; that's because the length of every vector denotes the possibility that the feature (nutrients) is present in that particular place in the picture, therefore it should be between one and zero. To accomplish this, use something termed the Squash method. This function just ensures that the length of every vector is almost 1 and 0 and does not delete the position data held in the vector's higher dimensions.

By applying the squash function to the vector form of the food images, it provides the probability of the nutrients. This probability value gives what amount of the nutrients presented in the input food image. It is necessary to predict the nutrients value which is used for classifying the food plan for the cancer patients.

The entire input to a capsule y is an addition of the weights of all forecasts from the capsules in the convolution kernel in the bottom layer for the capsules in these layers.

$$I_y = \sum_x a_{xy} \cdot \hat{P}_{y|x} \tag{1}$$

Where I_y denotes the overall input to capsule$y$; a_{xy} denotes the coupling coefficient reflecting the degree to which capsule x in the layer below activates capsule y; $\hat{P}_{y|x}$ is the prediction between capsules x and y and it is calculated as follows

$$\hat{P}_{y|x} = W_{xy} \cdot P_x \tag{2}$$

P_x is the capsule x output while W_{xy} is the network weight matrix. Remember that the length of a capsule is used in this model to forecast the possibility of the presence of an object. As a result, the activation function in this case is the nonlinear "squashing" function [7], which ensures that capsules with small vectors lead to lower possibility predictions while capsules with large vectors lead to high possibility predictions.

The squashing function is described below [7]:

$$S_y = \frac{\|I_y\|^2}{1+\|I_y\|^2} \cdot \frac{I_y}{\|I_y\|} \tag{3}$$

The small capsules are reduced to 0 length, whereas the large capsules reach a length near to 1. As a result, the length of a capsule's output vector can indicate the possibility of the retrieved local features' existence.

Each capsule in primary capsule layer is connected to every other capsule in Food Capsule layer. The predicted nutrients probability value is sent to the food capsule layer along with the patient details. For example, Pizza contains Fat-0.104, Protein-0.122 and Sugar-0 are transmitted to the food capsule layer.

3.4. Classification

The third stage of the proposed work is classification which is the final operation of the whole process. The final output is fully based on the previous layer output. Three layers are used in the classification phase to classify the food according to the patient health condition. The three layers are food capsule layer, Softmax preprocessing.

3.4.1 Food Capsule Layer

This is the first layer of the classification phase and fourth layer of the whole process. In this layer a major operation called routing preprocessing.

a. Routing Agreement

During this procedure, both primary layer capsules agree to choose the capsule in the subsequent layer as a probable picture outcome. This is known as routing by agreement.

In a CapsNet, instead of back-propagation like in a CNN model, routing by agreement is used to maximize the weight values (W_{xy}). During the routing process, a low-level capsule transfers its input value to an upper-level capsule. As a result, these weights connect the x main capsule (low level data) with the y secondary capsule (high level data). To put it another way, the weights give an affine transformation for learning part-whole relations. Here the low-level information or low-level feature is nothing but predicted probability value of the nutrients and high-level information or high-level feature is patient's health condition.

The classification was starts by routing process. The low-level features in the primary capsules that is predicted nutrients probability data is transferred to the high-level features in the food capsule layer that is patient data. If both information is strongly agreed with each other, then the input food item is classified to the good food and if not, it is added to the avoided list.

The coupling coefficients a_{xy} with all the advanced capsules y are totaled to 1 for every primary capsule x in the Primary Capsule layer using a Softmax activation function [8]:

$$a_{xy} = \frac{exp(b_{xy})}{\sum_z exp(b_{xz})} \tag{4}$$

Here routing logit b_{xy} is the log prior possibility that capsule x should be coupled to capsule y, and output a_{xy} denotes the normalized possibility that primary capsule x is linked to the advanced capsule y. The initial value of routing logit b_{xy} is set to

0 in first iteration, such that the probability of the primary capsule accepted by each advanced capsule are identical.

The dynamic routing technique iteratively refines the coefficient b_{xy} by assessing the agreement among the Primary Capsule vectors $\widehat{P}_{y|x}$ and S_y[9]. Dynamic routing adds a routing coefficient value to a y- digital capsule by the inner product among two vectors Eq (5). After calculating all of the primary capsule weights a_{xy}, every advanced capsule y of the Food Capsule is weighted by Equation (2).

$$b_{xy} = b_{xy} + \hat{P}_{y|x} \cdot S_y \qquad (5)$$

Primary Capsule $\hat{P}_{y|x}$ gives a good forecast for the meal capsule S_y if a good agreement is established. As a result, the coefficient b_{xy} increases significantly.

b. Margin Loss

Margin loss effectively implies that if an item of a given class is found in the image, the squared length of the associated vector of that element's capsule must be bigger than 0.9. Correspondingly, if the class item is missing from the image, the squared length of its corresponding vector should not above 0.1.

The following is the loss function calculated with a margin loss [8]:

$$L_m = T_m max(0, k^+ - \|P_m\|^2) + \lambda(1 - T_m) max(0, \|P_m\| - k^-)^2 \qquad (6)$$

$$T_m = \begin{cases} 1, & \text{digit of the class } m \text{ is present} \\ 0, & \text{otherwise} \end{cases}$$

When the m class happens, then $T_m = 1$ and k^+, k^- and λ are parameters that are determined in training. The complete loss is the total of all marginal losses in the final layer. The down-weighting of starting weights for missing classes is regulated by λ, with $\lambda = 0.5$ being a fair value.

For an instance, if the patient health data is: patient is in severe stage of cancer, and he/ she take the food which contains the nutrients level of Fat<0.05, Protein>0.109 and Sugar<0.106. But according to the previous layer example, if the input food image is Pizza which contains Fat-0.104, Protein-0.122 and Sugar-0.38. These values are predicted by the primary capsule layer and it is sent to the high-level features in the food capsule layer.

At the routing process the features are check with each other. That is the fat value of the food is 0.104 but the patient has to take the fat<0.05. Hence the routing agreement failed (0.104>0.05) for this feature. Then it routes the next feature namely protein. The protein value of the food is 0.122 and the patient has to take the protein>0.109. Here the condition is satisfied (0.122>0.109) and the routing process was agreed. Finally, the sugar value is routed to the high-level feature and the routing agreement is failed because the sugar level of the patient should be <0.106. But the food contains the sugar level 0.38 which means 0.38>0.106.

After the routing agreement process completed and based on the agreement the strong result was produced. That is if the routing process strongly agreed or not agreed with each other the food was send to classification layer with predicted values.

3.4.2 Classification Layer

The fifth layer of the proposed model is classification layer and it is also known as second layer of the classification phase. In this layer, both strongly agreed food and not agreed foods are classified for all patients based on the routing results.

Table 1. Example Classification

Patients	*Nutrients in Food (Pizza)*				**Routing Agreement Result**
	Fat	*Sugar*	*Sodium*	Zinc	Strongly Agreed
P1	NA	NA	A	A	Strongly Agreed
P2	A	A	A	A	Not Strongly Agreed
P3	NA	A	NA	NA	Strongly Agreed

From the above table 1 the classification layer classifies the food capsule layer's output based on the routing process results. Here A-Agreed, NA-Not Agreed. From the above example the food Pizza is strongly agreed with the patients P1 and P2. At the same time the Pizza is not strongly agreed with the patient P3 because of his/ her health condition. These results are sent to the next layer of the proposed model.

3.4.3 Output Layer

The last layer of the proposed work is output layer. It shows the results for the cancer patients based on the result of the classification layer. Here the food is strongly agreed with the patient health condition is added to the good food list and the food which is not strongly agreed with the patient health condition is added to the bad food list. The example result of the food suggestion for cancer patients were shown in Table 2

Table 2. Food suggestion for cancer patients

Patients	*Food Result (Ex: Pizza)*
P1	Good Food
P2	Good Food
P3	Bad Food

The above table shows the final output of the proposed model. If the patient health data and the nutrients in the food is highly correlated with each other it is good food and if not is bad food.

4. Efficiency Analysis

The performance of the proposed work is analysed in this section by comparing with the existing works. The proposed CapsNet based food suggestion system is compared with the other two existing works namely standard LSTM and CSW-WLIFC (Cauchy, Generalized T-Student, and Wavelet kernel based Wu-and-Li Index Fuzzy Clustering) [10]. The following terms are used for the efficiency analysis:

- Accuracy
- Loss
- Average running time
- Precision

4.1. Accuracy

Accuracy is one statistic for assessing classification models. Openly, accuracy is the percentage of correct predictions made by the model. Literally, accuracy is defined as follows:

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ prediction}$$

The accuracy of the proposed CapsNet was tested by comparing it with standard LSTM and CSW-WLIFC which is stated in the following table 3.

Table 3. Accuracy Comparison

Epochs	*Accuracy*		
	LSTM	*CSW-WLIFC*	*CapsNet*
1	0.81	0.83	0.90
5	0.84	0.82	0.92
10	0.82	0.85	0.95
15	0.87	0.87	0.92
20	0.9	0.88	0.94

From the figure 2, it is clear that the accuracy of the proposed work is increased when the number of epochs is increased. Because numerous convolution layers are employed in the proposed work for feature extraction. For feature extraction, convolution layers do not require manual interpretation. The convolution layer automatically extracts features, which enhances accuracy.

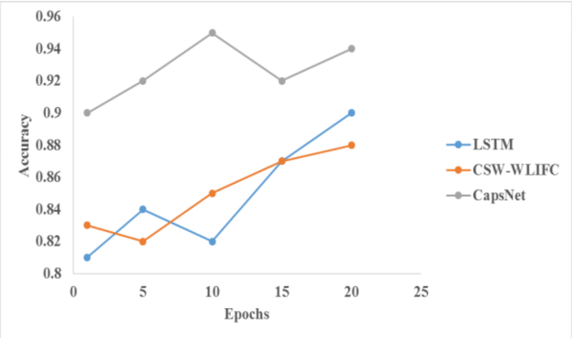

Fig 2. Accuracy Comparison

From the above observation, at the 20th epochs accuracy of the proposed CapsNet is 0.94 (94%) which is greater than the other techniques.

4.2. Loss

Loss is the penalty for a bad prediction. Loss value implies how poorly or well a model behaves after each iteration of optimization. The loss is 0 if the model's forecast is flawless; otherwise, the loss is bigger. Table 4 contains the loss values for Standard LSTM, CSW-WLIFC, and proposed CapsNet.

Table 4. Loss Comparison

Epochs	*Loss Value*		
	LSTM	*CSW-WLIFC*	*CapsNet*
1	0.017	0.022	0.004
5	0.029	0.033	0.022
10	0.035	0.037	0.029
15	0.030	0.042	0.035
20	0.033	0.038	0.025

Figure 3 shows the loss comparison between Standard LSTM, CSW-WLIFC, and proposed CapsNet. It shows that the loss of proposed CapsNet is smaller than the other two techniques. Due to the issue of losing certain spatial connectivity among the links is resolved because CapsNet saved all of the mined local attributes by simply changing the pooling approach by a dynamic routing procedure among the capsules.

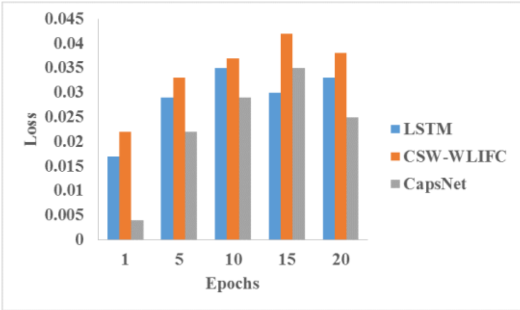

Fig 3. Loss Comparison

From the analysis the proposed CapsNet has the minimum loss value that is 0.025 at the 20th epochs than the other existing works.

5. Conclusion

Suggest a proper food plan for every patient is a challenging task in medical industry. The current work has presented a nutritious food recommendation approach for the cancer patients, according to their nutritional necessities and health condition. Deep neural networks are one type of technology that produces effective outcomes in the public health field. CapsNet is one of the most well-known image recognition networks. So CapsNet model is proposed in this study for effective food suggestion for the cancer patients. The proposed model analysed the patient health data then it classified the food according to their body condition. A capsule network for meal recommendation was created in this work employing the convolution, primary capsule, and food capsule layers. Feature extraction was done at the first two layers, while the food capsule layer is utilized to determine which foods are excellent and which are harmful. The constructed CapsNet correctly recognizes the problem. The suggested CapsNet's performance is compared to that of current approaches such as regular LSTM and CSW-WLIFC. When compared to those approaches, the suggested CapsNet performs well. The proposed model was 95% accurate. This article might be expanded in the future to train the suggested capsule network for all patients, not only cancer patients.

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