Study for Food Recognition System Using Deep Learning

Nareen O. M. Salim1*, Subhi R. M. Zeebaree2, Mohammed A. M. Sadeeq3, A. H. Radie4, Hanan M. Shukur5, Zryan Najat Rashid6,

1 Duhok Polytechnic University, 2 Duhok Polytechnic University, 3 Duhok Polytechnic University, 4 The Islamic University, 5 Al-Kitab University, 6 Sulaimani polytechnic university,

Emails: nareen.mohamad@dpu.edu.krd, subhi.rafeeq@dpu.edu.krd, mohammed.abdulrazaq@dpu.edu.krd, a.hussienradie@gmail.com, hanan.m.shukur@uoalkitab.edu.iq, zryan.rashid@spu.edu.iq

Abstract. Accurate dietary appraisal has been found by literature to be very significant in the evaluation of weight loss treatments. Most current methods of dietary evaluation, however, depend on recollection. The development of a modern computer-based food recognition system for reliable food evaluation is now possible across comprehensive mobile devices as well as rich Cloud services. Fixing the problem of food detection and identification in photos of different kinds of foods. Given the variety of food products with low inter-and high intra-class variations and the limited information in a single picture, the problem is complicated. By propose the overall application of multiple fusion-trained classifiers to achieve increased identification and recognition capabilities on characteristics obtained from various deep models. This paper studied various techniques of food recognition using different approaches and based on several variables, compared their effectiveness. Our study results demonstrate that deep learning overcomes other strategies like manual feature extractors, standard ML algorithms, as well as DL as a practical tool for food hygiene and safety inspections.

Keywords: Food Recognition, Neural Networks, Deep Learning, Classification, Clustering, Feature Selection.

1. Introduction

Good eating is essential to human health [1]. Natural products have been commonly used as foodstuffs and can also be manufactured to fulfill market demand. Food attributes such as type, structure, nutrients, and process types (natural products and refined food) are concerned with balanced diet issues. It is a fact that individuals have different eating patterns from other areas. Knowing the characteristics of foods (type, composition, nutrients and process types, etc.) The consistency and protection of foods for customers worldwide is essential for the inspection [2]. A realistic demand in everyday life is swift, precise, and automatic determination of food attributes. Modern techniques have been commonly used to detect food characteristics, including electronic noses, computer vision, spectroscopy and spectral imaging, and so on [3, 4]. A large amount of digital data relating to food properties can be collected through such methods. Data analysis of these methods is important because the enormous data volume includes a lot of repetitive and irrelevant material [5]. It is an urgent and vital challenge to deal with such a vast volume of data and extract useful features from the acquired data, and the complexity of bringing these methods into real-world use [6, 7].

Several data analysis methods, such as partial least squares (PLS), artificial neural network (ANN), support vector machine (SVM), random forest, k-nearest neighbor (KNN), and so on, A significant
amount of data has been developed for modeling to deal with [8-10]. Wavelet transform (WT), independent component correlation algorithm (ICA), scale-invariant feature transformation, robust speedup features, a histogram of a directed gradient, and so on, for feature extraction, such as primary component analysis (PCA) [11]. In dealing with such data, these methods have shown their tremendous value. Deep learning has been widely studied as an efficient machine learning algorithm [12]. It now attracts more interest from various fields such as remote sensing, agricultural development, medical science, robotics, healthcare, recognition of human behavior, recognition of voice, etc. In automatically learning representations of data (even for extraction of multidomain features), change learning, working with vast volumes of data, greater attainment output, and Increased Accuracy, deep learning has shown substantial benefits [13]. In most of the articles surveyed, (CNN) and its Algorithms obtained from derivatives were acknowledged, and the primary ways to In-depth features of digital input data are learned automatically for subsequent classification or regression tasks. CNN can successfully process the vast amount of data obtained by the quality and protection of food assessment instruments (electronic nose, digital cameras, spectroscopy, and so on) [14]. It should be noted that in image analysis (two-dimensional data), CNN is efficient and has been expanded to one-dimensional and three-dimensional data to handle more varied data formats [15, 16].

In this article, we reviewed a large number of recent articles on the APP on the deep learning of food stuffs, detailed the structure, training meth odds and the final assessment results of Deep learning for the processing of the food picture, spectrum, text and other details in each article surveyed.

The remaining part of this paper is organized as follows: Section 2 Background Theory. Section 3 Literature review. Section 4 Discussion, then a general conclusion, is provided in section 5.

2. Background Theory

2.1. Classification, Clustering and Feature Selection

When relatively few features are involved in classification, the efficiency, stability and utility of classification algorithms are improved. Thus, it has received considerable attention to choose relevant features for the construction of classifiers. A clarified taxonomy of algorithms was discussed; more recently [17]. There have been a number of options for the selection of functions, including wrapper techniques, vector supporters, neural network, and feature selection prototypes that are close to our own approach [18] [19]. The selection of clustering functions is generally done to maximize diversity. The basic for these methods consists of two steps: first, to create a feature space the corresponding distance measurement is selected; second, features are grouped in a clustering method; finally, to generate the selection result, the representative feature of each class is selected [20, 21]. Often the most relevant feature of the class label is the representative feature. In line with its correlations, hierarchically clustered the feature set and selected the best feature from every cluster for the final feature subset with a packing method [22]. While this procedure doesn't have to adjust parameters, it not only increases time and the learning method bias when introducing the packaging method. In a feature cluster framework, integrated sparse K means and Hierarchical clustering. Firstly, the set of functions is grouped into several functional clusters. Lasso type penalty factors are then employed to select from each cluster the representative features, which constitute the final subset of features [23, 24]. Using the agglomerative hierarchical clustering method in the supervised learning environment to divide the feature set and to set the final feature subset by removing features far from one another [7]. The maximum data coefficient can also be used to measure the correlation effect, cluster the relativity of the subsets, and then pick the centroid as the representative attribute of each cluster's cluster [25].

In the last few years, there has been a significant growth in the amount of high-dimensional data available on the Internet. Therefore, the large number of input features that is of great interest to researchers is difficult to cope with machine learning methods [26]. Pre-processing of the data is essential to use machine learning methods effectively. Functional selection is an essential feature of the machine's learning process and is one of the most common and important techniques of data preparation [27, 28]. It is also known in machine learning and stats as a variable selection, attribute
selection or variable subset selection. The detection and deletion of irrelevant, redundant or noisy data is a process [29, 30]. This process speeds up algorithms for data mining, enhances predictability and improves understandability. Features which do not provide any useful information are irrelevant and redundant features provide no more information than the features currently chosen [31, 32].

2.2. Food Recognition

Food identification is a challenging challenge since food products are presented; sometimes, they are different within the same group. A sort of issue with categorizing fine-grained pictures as the identification of food pairwise local characteristics that take advantage of eight specific food ingredients’ positional relationships [33]. The proposed multi-food image recognition system that detects first food recognizes color, texture, gradient, and SIFT extracted by several detectors using multiple kernels learning regions (MKL) [34]. The web application estimates nutritional balance as a food recognition device with food recording. The food is divided into 300 blocks, and five classes are further classified, such as staple, main dish, side dish, fruit, and non-food from each block’s extract color and DCT coefficients. Food identification and quantity estimation are part of the TADA dietary evaluation system [35]. Still, there are certain limitations on placing food on white dishes and taking food pictures for food quantity calculation, with a checkerboard. Image recognition processes are performed on servers in all the systems mentioned above, preventing operations from occurring interactive because of delays in contact. On the other side, for example, our device can identify food products in real-time on the customer side, which does not require contact with external computer resources and allows customers to use it interactively [36].

2.3. Deep Learning

Therefore, since some of the approaches discussed in this article depend on the specific internal aspects of deep learning, we include a brief background on deep understanding. You will find more information in the reference texts [37]. A prediction algorithm for deep learning, also referred to as a model, consists of several layers, as displayed in fig. 1. The data as input passes through the layers during deep learning inference, and every layer presents multiplications of matrices on the data. Usually, a layer's output is the input to the layer below [38]. The result is either a function or output of classification after the final layer processes data. When the model contains several layers in succession, the neural network is a deep neural network [39]. A particular example of deep neural networks is when coevolutionary filter operations are used in matrix multiplications, usual in Deep Neural Network (DNNs) built for video and image processing [40]. These methods are called coevolutionary neural networks (CNNs). DNNs are often explicitly developed to predict time series; these are recurring neural networks (RNNs). To maintain the state and make sequential input predictions, which have circles in their layer links [41]. The computation continues in reverse order in in-depth learning training. In order to optimize every layer of matrix multiplication parameter, several passes are made over the layers, starting with the final layer and finishing with the first layer, given the ground-truth training labels [42]. Usually, stochastic gradient descent is the algorithm used. A randomly selected "mini-batch" sampling of samples is selected in each phase and the grades are revised in the area that reduces training failure (where the loss of training is defined as the difference between the predictions and the reality of the ground) [43].

![Figure 1: DNN Image Classification Example](image-url)
2.3.1 Deep Learning (DL) Efficiency Assessments

Both supervised learning and unsupervised learning can be carried out using deep learning success metrics depend on the unique app domain of the application in which DL is implemented and tested how much the intended location of the object overlaps with the position of ground-truth distributed over many groups of objects [44]. A bilingual evaluation of the understudy score metric which compares a candidate translation with several reference translations of ground-truth, will determine machine translation accuracy [45]. Other non-application-specific general device performance metrics include throughput, latency, and electricity. To conduct both supervised and unsupervised processes of learning, DL can be used. For example, accuracy can be determined by the mean average accuracy of object detection. Estimating how much the predicted position of objects overlaps with the location of ground-truth, averaged over many object categories. By bilingual evaluation of the understudy score metric, the machine translation accuracy can be determined [46].

2.4 Applications of Deep learning in food processing

Deep learning was superior technology for multiple active objects, image analysis and so on. The improvement of DL-based studies in recent decades has been an absurd climb. DL plays a key role in the development of food applications, such as vegetables, fruits, palm oil, fish, and much more. In the following sub-sections, certain relevant implementations are referred to.

2.4.1 Deep Learning in the processing of fruits

The fruit is a form of raw human food. Various issues are faced with both the sales and production of fruit, such as disease prevention, bruise, rats, etc. The fruit, however, is a high-speed array of farming materials. Some of the concerns considered are nutrient quality, safety assurance, and the recency of fruits. Quality identification of both vegetables and fruits are a hot and recent research topic that is challenging. DL has now been used extensively as a non-critical and robust method of recognizing fruit quality to solve Issues such as assortment categorizations, nutrient content prediction, infection, or identification damage, in conjunction with image processing sensing techniques. The DL plays a critical role while processing fruits such as cherry, lemon, date, walnut, banana, avocado, apples and pear, capsicum, mango, and many others [47].

2.4.2 Deep Learning in the processing of vegetables

Vegetable consumption is an essential part of a balanced diet as it provides abundant vital nutrients for humans. For example, diseases, infections, Pests, damage, and many more can impact and decrease both the financial value and customers' wellbeing. Most researchers have demonstrated DL's effectiveness in overcoming the problem of measuring and an evaluation of the number of vegetables [48].

2.4.3 Deep Learning for Palm Oil Production

Data collection from palm oil trees in agricultural estates is needed to increase revenue growth. In the plantation organization, the identification and inclusion of palm oil are essential. Typically, the majority of past studies have focused on the detection of palm oil trees that do not consist of overlying crowns. A lack of research uses DL advances to create different identification schemes for young and fully grown oil palms. To fill this gap, [24] have attempted to separately distinguish young and gowned oil palms using two distinct CNN's [49].

2.4.4 Deep Learning for fish

During the year, fishing has become an essential resource of the right nutrients in human beings' diet. The DL has remained an essential method for fish processing. Rauf et al proposed an opinion. Fish class categorization technique that relays five intensely prohibited subnet hierarchy chunks on supervised 32-layer VGGNet. The authors' objective was to add a DL model relay on the CNN technique for fish species identification. To enhance categorization efficiency by specifically including 4 CNN layers in personal level training, they put in-depth supervision on the VGGNet system.
has changed them Pak dataset to test the planned 32-Layer CNN model's performance. They considered images to have 915 pictures, along with six distinct groups and three image views. The study concluded that, compared to existing techniques, the projected approach achieved better performance [50].

3. Literature review
Ciocca et al. [51] A new dataset has been introduced, featuring 20 different foods from 11 different countries, ranging from solid, sliced to smooth pastes in fruit and vegetables. Author experiment in three separate recognition tasks with most widely used architectures from the Coevolutionary Neural Network (CNN), including divisions of food, food states and all foods and states. Because in practice the absence of classified data is normal, the author utilizes deep features derived from the CNNs in combination with the SVMs as an alternative to the end-to-final classification. As an alternative, this classification is often not supported. Author also equate deep characteristics with a number of handmade features. Sees tests confirm that the profound attributes of the product group or the food status in question outperform handmade features in all three classification tasks. Finally, we measure the widespread capacity of deepest functionality by using another dataset of food statement which are widely made available. This latest experiment illustrates the success obtained by the state-of-the-art approach of the features generated from a CNN formed on our proposed dataset. This shows that our profound characteristics are strong in relation to the CNN's never seen data.

K Srigurulekha et al. [52] The category of food representations using coevolutionary neural networks is implemented with a new approach. Not like the standard neural artificial network, coevolutionary neural networks is genuinely able to calculate the score work from image pixels. Many such layers are available and the output is concatenated in sections to structure the last yield tensor. The MAX pooling technology is utilized for the isolation and preparation of the model from critical images. We achieve 86.85% accuracy for the FOOD-101 dataset in this proposed method.

Azizah et al. [53] used Convolutional Neural Network's deep learning architectures (CNN), to detect mangosteen detection. About classifying pictures, CNN has proven to be very reliable. To verify data accuracy, this CNN approach is implemented using the 4-fold Validation Cross. The initialization of the configuration of the parameters accelerates the stage of network training in the preparation of the CNN architecture model. Results of the CNN algorithm studies showed a 97% efficiency of mangosteen fruit defect detection.

Lie et al [54] created new algorithms for visual food recognition based on deep learning to achieve best-in-class accuracy in recognition, and designing a food recognition system to solve some of the inherent problems of the conventional mobile cloud computing paradigm, such as excessive system latency and poor mobile machine battery life, using the edge computing-based service computing model. Authors have done detailed studies with real-world proof. Our observations have shown 3 targets: 1- Existing food accuracy tests are outperformed, 2- the reaction time is decreased according to the minimum number of current methods and 3- energy consumption is minimized, which stays close to the state-of-the-art minimum.

Pouladzadeh et al. [55] suggested an assistive calorie measurement method in this study to help patients and physicians excel in combating diet-related health conditions. The device proposed by the study operates as a smartphone application that automatically monitors calorie intake based on a picture taken by the consumer of the food. By proposing a cloud-assisted mobile food recognition system, the authors discuss these challenges in this task. The results show that in non-mixed plates, single food portions, and mixed food plates, the accuracy of the recognition stage within this cloud-assisted application is improved compared to Support Vector Machine (SVM). Also, by applying a deep neural network, food recognition accuracy in single food portions is improved to 100%.

Pandy et al. [56] To recognize food, a multilayered CNN was developed. Two separate images were presented: Food-101 and a database of Indian foods, which later had 50 categories, each with 100 images. The suggested algorithm used the deep architecture of CNN AlexNet as the basis. A multilayered CNN pipeline was created to integrate three separate subnetworks (AlexNet, GoogLeNet, and ResNet). Top-1 % of 72.12 %, Top-5 % of 91.61 %, and 95.95 is the Accuracy of Top-10 % For the Food-101 database, and for the Indian food database, 73.50%, 94.40%, and 97.60%, respectively,
in this study excellent prediction results were achieved. In both the two datasets, the proposed ensemble net outperforms the CNN model with one subnetwork for all levels. Aguilar et al. [57] proposed a mix of several classifiers that supplement each other on the basis of Convolutional models to ensure efficiency improvements. The assessment of our methodology is carried out in two public datasets: Food-101 as a dataset for a large range of fine grain dishes and Food-11 as a high-level group of high-level food products.

Pan et al. [58] proposed a new system called Deep Food that extracts rich and effective features from a deep learning dataset of images of food ingredients by applying advanced machine learning techniques and enhances the average accuracy of multi-classification by applying advanced machine learning techniques. Many transfer learning algorithms concentrated on for deep feature extraction, CNNs have been leveraged. Then, A multi-class classification algorithm is used depending on the results of the classifiers on each deep feature collection. The DeepFood Scheme is evaluated on the basis of a multi-level dataset, which comprises 41 food components and 100 images per class. The findings of experiments demonstrate the efficacy of the DeepFood method for multi-class food ingredient classification. This model blends ResNet deep feature sets, IG selections and the superiority of SMO in the identification of food ingredients compared to a number of known works in this area.

Heravi et al. [59] emphasized the construction of a basic network thus maintaining less parameters model performance in realistic APP consideration for cost, processing speed, and hardware requirements. Network planning is normally done by reducing the mistake between the source and the ground truth. They proposed a new idea, though, which transferred information from the large-scale CNN (compressed GoogLeNet architecture") to a single model (with much less parameters than the CNN trainer). The data transfer task for teachers of CNN-by-CNN trainees was to perform the correct estimate.

Martinel et al. [60] Presented a modern deep system built to accommodate the arrangement of the foodstuff. Author focuses on vertical features common to many classes of food (i.e., 15 percent of the whole data in current datasets). To achieve the final target, we first add a slice block to capture this specific knowledge. We then take advantage of the recent success of deep waste blocks and combine them into a sliced convolution to give the grades. Extensive evaluations of three standards have demonstrated that our solution exceeds existing approaches (e.g., a top-1 accuracy of 90.27 percent on the Food-101 dataset).

Ciocca et al. [61] The usage for food identification and recruiting of CNN-based features has been studied. For this purpose, the Food 475 database, the largest publicly accessible food databases with 475 food groups and 247 636 photographs, was first introduced. In terms of the total number of images, the number of domain classes and the number of classes we then describe the representation of the food domain of various food databases. A CNN built on the 50-layer architecture residual network and developed on food-data bases with various food-Domaine representatives would be used to extract various features. For food classification and recovery activities, author test these functions. The results suggest that features from the Food-475 data sets outperform others, which show that we need broader food databases to meet the food identification challenges and that the database generated is a step forward.

Zhang et al. [62] designed a neural network with 13-layer convolution (CNN). Three types of data increase methods were used: image rotation, gamma correction and injection noise. Max pooling with average pooling were matched as well. In the case of the 128 minibatch scale CNN was used for the stochastic gradient descending at momentum. Our method's average accuracy is 94.94%, at least 5% over state-of-the-art approaches. Author also validated the optimum configuration for this 13-layer. The GPU will accelerate training data to 177 times and test data to 175 times. We found that data increase would improve overall accuracy. Our method is effective in the classification of images based on fruits.

Williams et al. [63] Presented an assessment of the architecture and efficiency of a new kiwi harvest robot in the pergola type designed to function independently. The harvester consists of four robotic weapons specially designed for the harvesting of kiwi-fiber, each with a novel end-effector designed to ensure a healthy harvest of kiwi-fi. In deep neural networks and stereo for reliable detection and location of kiwis under real-world lighting conditions, the vision system exploits the recent
developments. In addition, a new complex fruit programming scheme was built to coordinate the four weapons during the entire harvesting period. The harvester's output was assessed in a commercial orchard setting through a rigorous and practical field test. Results indicate that 51.0% of the total amount of kiwifruit can be harvested in the orchard, with an average cycle time of 5.5s/fruit, with the presented harvester.

Mezgec et al. [64] proposed studies tested the combination of an existing food-choice research approach ('fake food buffet') and a validated one to automate the processing and interpretation of data using modern food-association technologies. This incorporates the use of deep learning, nutritional compatibility, and natural language processing for the identification of fake food. The first is unique because it uses a single deep network for dividing and classifying images at the pixel level. Measures based on the pixel precision and cross-section over Union have been applied to determine its efficiency. First, the food match identifies each of the food items in the picture and then compares their composition details to food items, taking into account their names and descriptors. The final accuracy of the deep learning model educated on photographs of false food obtained by 124 research students with fifty-five food groups was 92·18%, while the food match was carried out with an accuracy of 93%.

Reddy et al. [65] Proposed a calorie-measuring device to upload a food-specific image to the consumer, thus predicting the amount of calories in a food image being posted. It is a multi-task device that often shows weekly figures about how much calorie the consumer consumes and how more/less calories are required in order to prevent obesity-related illnesses such as cardiac crises, cancer etc. Author have developed a dataset of food pictures from existing datasets for the detection of complex images of 20 classes and 500 images per class. To extract features and identify images, we have developed our own architecture for Convolutional Neural Network in 6 layers. The findings from our experiments with food accuracy showed 78.7% with a training accuracy of 93.29%.

Teng et al. [66] Proposed the architecture for Chinese food recognition for a lightweight, effective and resource-limited nerve network architecture. Our network architecture is designed to model and execute a bag-of-feature-like process pipeline. Like other convolutionary neural networks, the key benefit of the proposed design is its ability to optimize the whole network unilaterally through the back propagation which is crucial for accuracy in recognition. In an effort to explore comparisons and to recognize influences that affect the accuracy of identification, author further compares and correlates our architecture with the standard Bag-of-Features model. With a newly developed Chinese image dataset consisting of 8734 images from 25 food groups, this proposal architecture with a 5-layer depth convolutionary neural network achieves the top-1 accuracy of 97.12 percent and the top-5 accuracy of 99.86 percent. Our experimental findings indicate that the proposed CNN compact architecture is feasible to solve a challenge and achieve real-time efficiency.

Knez et al. [67] Evaluated the latest mobile device-developed food object recognition systems. The assessment was performed using the method of food identification to analyze each device. The entire identification procedure was split into six different phases: retrieval of images, image analysis, image segmentation, extraction of features, image classification and volume estimation. Through means of analyzes, authors categorize structures for the identification of mobile foods: recorders, suggesters and clinical respondents. Each category has a separate situation and can help determine the characteristics of a specific system.

Alajrami et al. [68] A solution proposed to allow people to decide more precisely the form of tomatoes by developing deep learning models (coevolutionary neural networks), educated and validated, has been evaluated. In addition, with our network of four CNN and four Max pooling layers, we used this trained model, for prediction of the kinds of (previously unseen) tomato images, which agree the intake of tomatoes with seven different species. The consistency of the tests was 93%.

4. Discussion
The exponential growth of the Internet and of social media, smartphone applications and other technology has created more diverse data collection methods that allow more people to take part and provide food information such as photographs and text explanations, to facilitate the emergence of even greater datasets in the future. Food quality and safety inspection by experts and organizations
around the world are carried out using their own data sets. There are restricted data collection capacity on a single individual, research team or organization. It is anticipated that new sensors and instruments from international customers, investigators and institutes will embed data databases relevant to food in the broader global databases. This data sets can be processed easily to the benefit of deeper learning and are beneficial to researchers and food institutes.

From the previous section, it can be seen that researchers have employed different types of techniques and algorithms in Food Recognition fields. Scientists have issued a list of their recommendations upon studying theirs. Table 1 of the paper explains the explanations explained in the paper. The plan should include a comparison of the success and commonalities in the methodology of Food Recognition. The researcher used the Dataset, algorithms, implemented system, accuracy and the Significant Satisfied Aims approach to analyse the results.

It is evident from the table that researcher depend on different Dataset like Mangosteen detection, Food 101, Indian foods, Food-11, food dataset rather than remaining dataset. Depending on the scientific area of Food Expressions Algorithm, CNN, DNN, SVM, PCA, MLP, KNN are most algorithms used in this field. The system which implementing their work is booth mobile and computer system rather than remaining system. Also, researcher get accuracy in their work between 70% - 100%. By using this methodology and techniques, both researchers have strong structures, frames, and functions. However, researchers’ trend has been oriented for modern Food Recognition fields.

### Table 1. Formatting sections, subsections, and subsubsections.

| Ref.          | Dataset                | Algorithm                | Systems               | accuracy | Significant result                                                                 |
|---------------|------------------------|--------------------------|-----------------------|----------|----------------------------------------------------------------------------------|
| Ciocca et al. [51] | Creat dataset 20 different foods | CNN, SVM                | mobile system         | -------- | A new dataset has been introduced, featuring 20 different foods from 11 different countries, ranging from solid, sliced to smooth pastes in fruit and vegetables. |
| Srigurulekha et al. [52] | Food 101             | CNN, k-NN, SVMs          | Computer software.    | 86.85%   | K Srigurulekha et al. [52] The category of food representations using coevolutionary neural networks is implemented with a new approach. |
| Azizah et al. [53]   | Mangosteen detection  | CCN                      | Computer software     | 97.5%    | Used the deep learning architectures of the Convolutional Neural Network (CNN) for mangosteen identification recognition. |
| Lie et al [54]      | real-world data       | deep learning            | mobile cloud computing | -------- | A new dataset of 20 different foods, ranging from solid, sliced to smooth paste in fruits and vegetables, has been launched. |
| Pouladzadeh et al. [55] | 7000 images           | SVM, deep neural network | smartphones           | 100%     | Suggested an assistive calorie measurement tool for patients and doctors to improve their quality in the fight against dietary health conditions. |
| Pandy et al. [56]   | Food 101, Indian foods | multilayered CNN         | Computer software     | 97.60%   | A multi-faceted CNN has been developed to identify food. |
| Authors | Dataset/Dataset/Model | CNN | Computer 
------- | ------ | ------ | ------ | ------ | ------ |
|---------|----------------------|-----|--------|
| Aguilar et al. [57] | Food-11 Food-101 | CNN | Automatic monitoring Computer | The mixture of multiple classifiers, based on the Convolutional model, has been suggested in order to ensure changes in performance. |
| Pan et al. [58] | multi-class dataset | CNN | Computer framework | Deep Food proposed a new method extracting rich and efficient characteristics from a deeper learning data collection of food images. |
| Heravi et al. [59] | UECFood-256 | CNN | Computer and network | The development of a simple network was stressed, thus retaining lower parameter model efficiency in terms of expense, process speed and hardware specifications in practical APP consideration. |
| Martinel et al. [60] | UECFood100 UECFoo256, Food-101 | (DNN) | Mobile device | 90.27% | Presented a modern deep system built to accommodate the arrangement of the foodstuff. |
| Ciocca et al. [61] | UECFOOD-475 | CNN | Online Web service | The usage for food identification and recruiting of CNN-based features has been studied. |
| Zhang et al. [62] | VegFru | CNN | Computer system | 94.94% | designed a neural network with 13-layer convolution (CNN). |
| Williams et al. [63] | "kiwi-fruit" harvesting robot | PCA, CNN, MLP, KNN | Robot system | 97.5% | Presented an assessment of the architecture and efficiency of a new kiwi harvest robot in the pergola type designed to function independently. |
| Mezgec et al. [64] | food dataset | FCN | Smartphone e | 93% | The proposed studies tested the synthesis of the current food-choice ("fake food buffet") and established methodology to automate data collection and analysis using new technology of food-association. |
| Reddy et al. [65] | built a dataset | CNNs of 6 layers | Smartphone e | 93.29% | Proposed a calorie-measuring device to upload a food-specific image to the consumer, thus predicting the number of calories in a food image being posted. |
| Teng et al. [66] | Chinese food | CNN-5 | limited platforms | 99.86% | The Chinese Food Recognition Architecture was proposed for a light, efficient nerve network architecture. |
5. Conclusion
In this article, we reviewed a large number of recent articles on the APP on the deep learning of food stuffs, detailed the structure, training meth odds and the final assessment results of Deep learning for the processing of the food picture, spectrum, text and other details in each article surveyed. As far as efficiency is concerned, we likened the deep learning to other common approaches and observed that in these tested studies the deep learning approach delivers better outcomes than other methods.

This paper addressed important Food Recognition. The literature review indicated that various active mechanisms contribute to Food Recognition. To achieve this aim, the researchers have successfully employed numerous techniques and algorithms. Effective food recognition has also been established, for example Build an automatic tray analysis pipeline to input a tray picture, identifies the regions of interest and predicts the food class of each country and the data collection was benchmarked by the analysis. The study proposed tested a hybrid of the current approach to food choiring ("fake food buffet") and a proven approach for automating data collection and analysis utilizing new technology for food association, suggested an assistive calorie measurement tool for patients and doctors to improve their quality in the fight against dietary health conditions, suggested a smaller and powerful neural network architecture that is more relevant to resource constrained systems in the Chinese food recognition. Adding to that, it can conclude that CNN, DNN, SVM, PCA, MLP, KNN is the most suitable techniques for Food Recognition. By using this Dataset, Mangosteen detection, Food 101, Indian foods, Food-11, food dataset.

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