IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁘ Impact Factor 7.39 ⁘ Vol. 11, Issue 9, September 2022

DOI: 10.17148/IJARCCE.2022.11905

Real-time Food Recognition and Classification System to Aid Diabetic Patients - Systematic Review

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Abstract: Food Recognition is a computer vision application that has gained huge research interest. Food recognition and classification is a major task in managing health conditions and most importantly in assisting Type 1 diabetic patients in taking decisions on the right food to eat that will not worsen their health conditions. Diabetes has become a global health challenge threatening the well-being of millions of people across the world. Food recognition systems aid diabetic patients in monitoring what they eat, managing their chronic health conditions, and improving their quality of life. This paper presents an extensive review of food recognition and classification methods to aid diabetic patients and the food geographical regions of available datasets already studied. The review explores existing mobile and Desktop food recognition systems and diabetes self-care management applications. The analysis presented in this paper gives the following new insights: the most performing food recognition Methodologies that have been developed; the existing food datasets and the unexplored research areas. The findings in the literature reviewed show that Convolutional Neural Network (CNN) recognition techniques are widely applied in food recognition and classification systems compared to the Bag of Features (BoF) method. Also, the main challenge in this review is the functionalities of the available diabetes applications in the market and it was discovered that none offers recognition of Nigeria Foods to aid diabetes patients.

Keywords: Diabetes, food recognition, food classification, glycemic index, sugar level, deep learning, convolutional Neural Network

I. OVERVIEW

This research paper presents a systematic review of food recognition and classification to aid diabetes patients. It also looked at the impact of food classification that helps diabetes patients in most cases in incorporating the various self-care and monitoring components into their daily lives. The theoretical introduction to food recognition and classification of sugar content for monitoring diabetes patients is presented in Section II. Section III reviews related works. Section IV describes the methodologies applied in food recognition and classification. Section V discusses the datasets available for food recognition, Tables 1 and 2 summarize the methods, datasets, and food recognition types in the reviewed literature. Section VI highlights the research gap.The summary was covered in Section VII.

II. INTRODUCTION

Diabetic conditions and their complications have affected the present society's economic status and indeed have resulted in adverse impacts due to the cost of treatment, social costs, and loss of lives. To control this, diabetes care requires an appropriate strategy in setting goals for dietary awareness and physical exercise arrangements, appropriate medications, appropriate self-monitoring of blood sugar levels, and food assessment [1]. Diabetes is a chronic illness that requires the patient to be vigilant in monitoring and managing their glycemic fluctuations by taking medication, sugar-free diets, and exercise. These patients in most cases experience challenges in incorporating the various self-care and monitoring components into their daily lives. Patients monitoring their blood sugar levels daily, also known as self-testing, is an essential part of managing diabetes. This helps to provide relevant information to the patient's doctor to enable evidence-based care and diagnosis which is vital for the early detection of insulin resistance. The increasing prevalence of diabetic risk factors and lack of awareness has been the most critical obstacles to overcoming diabetes. Diabetes is of two types namely: Type 1 and Type 2 diabetes [2]. Type 1 diabetes develops when the body fails to create insulin. Therefore, the patient is required to take insulin infusions and maintain normal blood glucose levels and having an ordinary blood test. Type 2 diabetes develops when the patients have insulin obstruction or the body neglects to perceive and use the insulin

International Journal of Advanced Research in Computer and Communication Engineering
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properly, causing sugar to develop in the patient's circulation system. To keep the blood glucose at everyday levels, the patient's pancreas at first makes additional insulin to make up for it, yet over the long haul, it cannot discharge the necessary amount needed to keep the blood glucose. Type 2 diabetes can be constrained by good dieting propensities and improved body exercise. To stay free from diabetes complications, the patient is required to control their blood glucose to limit the formation of hyperglycemia [2].

According to [3], Diabetes Online Community (DOC) is a conglomerate of persons with diabetes committed to imparting data and experience about living with diabetes and its treatment. DOC recommends that patients carefully check what they eat when dealing with their glycemic vacillations. Studies have shown that using smartphones for Type 1 diabetic self-administration has demonstrated to be viable and productive in dealing with chronic disease. Real-time Food recognition and classification are more effective for diabetic patients in accessing the glycemic index level of their food. The significant number of diabetic patients worldwide, along with their demonstrated powerlessness to evaluate their eating regimen, raised the need to develop systems that will assist Type 1 Diabetes patients in sugar level assessment of their food before eating. A wide range of cell phone applications has been proposed in [1]. The rise in mobile phone graphics processing capabilities and the new advances in computer vision allows the presentation of picture/video examination-based applications for diet assessment. Real-time food pictures taken from a camera device are the inputs to the food recognition model. The picture is processed by the model either locally or on the server-side to determine the class of food it belongs to for the sugar level assessment.

The study in [4] reveals that using a smartphone application for diabetes management resulted in a statistically significant improvement in adults with Type 1 diabetes. The limitations in developing a mobile-friendly deep learning algorithm at that time led to several challenges in the practical development of edge-based applications. The limitations include the under listed factors [5]: • No clear understanding of which architecture is suitable for mobile system development; • Training with limited data; • Difficult to achieve real-time applications; • Need for more powerful portable models. Traditionally, CNN models run-on high-performance computing servers due to hardware requirements and are unavailable to operate on smartphones. To overcome these issues, there is a vital need for a machine learning framework suitable for smartphones to perform computing-intensive Computer vision tasks, such as object recognition.

III. LITERATURE REVIEW

Various approaches have been used to recognize and classify foods based on their sugar level. The approaches can generally be classified into Convolutional Neural Network, Histogram of Gradient (HoF), Bag-of-Features, Colour Histogram, K-Nearest Neighbour (KNN), and Support Vector Machine (SVM).

The research work in [6] proposes a food dataset called Foodx-251 for a food classification application. The food dataset contains 158,000 pictures of food images downloaded from the web. The dataset was trained using a state-of-theart deep model. The dataset development required advanced computer vision models and datasets for evaluating these models. The paper focused on FoodX-251, a 251 fine-grained food categories dataset with 158k images collected from the web. The work outlined the procedures for creating the dataset with deep learning models. The FoodX251 Dataset is available for download. However, the proposed application does not classify the food dataset based on their sugar level.

In [1], proposes a BoF-based system for food image classification; this is the first step toward improving a portable application and providing dietary advice to diabetic patients through automatic glucose counting. The improved framework uses SVM for the food classifier. The strength of the system is the recognition of food types from new, and unknown images, while the weakness of the system is the limitation of the dataset to only European foods and the recognition is not done in real-time.

According to [7], an Android application for Children with Type 1 diabetes was proposed. The datasets were locally developed for Kenyan Foods because most of the existing applications are meant for users targeted in the developed world context. Through the study, a logging application on an Android Smartphone was designed and developed for Children with Type 1 diabetes dwelling in a developing world to help them in diabetes self-management. The work also investigates the changes related to diabetes self-management and user satisfaction. The survey results for user satisfaction showed that 81.7% of respondents had positive changes in their clinical course of diabetes self-management.

In [8], the authors addressed the following issues on deep learning for food recognition: (1) to develop novel deep learning-based visual food recognition algorithms to obtain high detection accuracy; (2) to design a food recognition for diet assessment system employing mobile-cloud based computing, to prevent latency and low battery life of mobile devices. They conducted experiments with real-world datasets. The results showed greater recognition accuracy in the edge computing device.

The research in [9], proposes a small and efficient convolutional neural network architecture for the Chinese food recognition system. The network architecture based on the Bag-of-Features model approach. Like other convolutional neural networks, the proposed architecture is optimized through backpropagation, which is critical to

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recognition accuracy. The paper compared and correlated the architecture with the traditional Bag of Features model to investigate their similarities and identify factors that influence the recognition accuracy. The proposed architecture with a 5-layer deep convolutional neural network achieves an accuracy of 97.12% on a newly created Chinese food image dataset composed of 8734 images of 25 food categories. The experimental result demonstrates the feasibility of applying the proposed CNN architecture to a challenging problem and achieving real-time performance.

The authors in [10], studied the application of CNN-based features for food recognition and retrieval. They introduced a Food-475 database, which is the largest publicly available food database with 475 food classes and 247,636 images obtained by merging four publicly available food databases. Different features were extracted using CNN based on the ResNet with 50 layers architecture and trained on food databases. The results demonstrate that the features extracted from the Food475 database outperform the other research work indicating that larger food databases are required to tackle the challenges in food recognition.

The authors in [11], focused on developing a mobile-friendly, Middle Eastern food recognition application for assisted living purposes. Developing CNN architectures on mobile platforms requires a low-latency, high-accuracy food classification system. Thus, they opted to utilize the Mobilenet-V2 deep learning model. The number of used Middle Eastern food datasets samples is relatively large and imbalanced. To compensate for this problem, they utilized data augmentation methods on the underrepresented classes of food datasets. The experimental results show that using MobilenetV2 architecture for food recognition is beneficial in terms of accuracy and memory management. The model achieved 94% accuracy on 23 food classes, and the application benefits the visually impaired in automatic food recognition via images.

As seen in [12], the authors developed a deep model-based food recognition and dietary assessment system to study and analyze food items captured by smartphones. They proposed a three-step algorithm to recognize multiple food images by detecting candidate regions and using deep CNN for object classification. The system maps each image region into feature maps, classifying them into different food categories and locating them in the original images. Then, the system analyzes the nutritional ingredients based on the recognition results and generates a dietary assessment report by calculating the number of calories, fat, carbohydrate, and protein. Experiments were conducted utilizing two popular food image datasets; UEC-FOOD100 and UEC-FOOD256. Also, a new dataset was generated based on FOOD101 with bounding.

The paper in [13], proposes a food recognition system based on the BoF model for diabetic patients. The extensive investigation is carried out based on 5000 datasets for components and parameters inside the BoF architecture to be optimal. The testing and comparative assessment of three extraction techniques based on a key point, fourteen local image descriptors, two clustering techniques for visual dictionary creation, and six classifiers are carried out. The food image recognition and classification system are comprised of two phases. In the training phase, the food recognition system learns from the obtained knowledge, and in the testing phase, food types are recognized by the system from new, unknown images. The proposed system is appropriate for dealing with generic food descriptions because the BoF model and the BoF architecture contain optimal parameters and components. The BoF display has demonstrated the capacity to manage high visual assorted variety. Furthermore, the effects of parameters such as the number of key points extracted, the size of the descriptor, and the number of visual words were demonstrated.

The paper in [14], presents a novel system based on machine learning that automatically performs accurate classification of food images and estimates food attributes. The paper proposed a deep learning model based on a CNN architecture that classifies food into specific classes. The main objective of the proposed method is to improve the accuracy of the pretraining model. The designed prototype system is based on the client-server model. The user image detection request is sent over a network to the server side where they are processed. The prototype system is designed in three stages: a pre-trained CNN model training module for classification purposes, a text data training module for the attribute estimation model, and a server-side module. They conducted experiments on thousands of food images and the training showed high accuracy.

As developed in [15], a food recognition and assessment system using CNN was trained on food images collected by taking pictures or searching web images and built a food dataset used in training a recognition model for Korean food. Image augmentation techniques were performed on the datasets to increase the dataset size. The dataset used in the training consists of more than 92,000 images classified into 23 groups of Korean food. The images were down-sampled to a fixed resolution of 150 × 150 and then randomly divided into training and testing groups at a ratio of 3:1, resulting in 69,000 training images and 23,000 test images. They used a Deep Convolutional Neural Network (DCNN) for the complex recognition model and compared the results with those of other networks: AlexNet, GoogLeNet, Very Deep Convolutional Neural Network, VGG, and ResNet, for large-scale image recognition.

As seen in [16], a Region-Level Attention Network (RLANet) is proposed for food and ingredient joint classification. The system is composed of two-stage modules. At the Feature Extraction Stage, a two-layered structure was designed to extract global food features and local-region ingredient features under the supervision of the ground-truth label. They proposed a Region-Weighted Module (RWM) at the fusion stage to obtain relation fusion features for

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better performance. Their experimental results demonstrate that the model achieves state-of-the-art performance in ingredient recognition on the Chinese Food dataset VIREO Food-172. The results of food classification are impressive.

In [17], proposed a CNN-based multiple-dish food recognition model using the EfficientDet deep learning (DL) model. The designed model was developed taking based on three types of meals, namely: single-dish, mixed-dish, and multiple-dish, from local Taiwanese cuisine. The results show high mean average precision (mAP) = 0.92 for the 87 types of dishes. With high recognition performance. They were optimistic that the proposed model has the potential for effective dietary management. They suggest that future work should focus on improving the performance of the algorithms and integrating the system into a real-world mobile and cloud-computing based system to enhance the accuracy of current dietary intake reporting tasks.

The authors [18], proposed a smartphone-based system for recognizing the food dishes and fruits for children with eye problems. The Smartphone application utilized deep CNN model for recognizing the food item from the real-time images. Also, they developed a new deep convolutional neural network (CNN) model for food recognition through the fusion of two CNN architectures. The applied ensemble learning approach in developing the new deep CNN model. The deep CNN food recognition model is trained on a customized food dataset. The customized food dataset consists of 29 classes of food dishes and fruits. In addition, the authors analyzed the performance of the deep CNN models for food recognition using the transfer learning method. The model achieved a food recognition accuracy of 95.55 % in the customized food dataset. Finally, the authors evaluated the performance of the proposed deep learning model on publicly available food datasets.

In [19], proposes a framework for diabetes management problems dedicated to achieving to following objectives: to build a Tensorflow neural network model for food classification; to allow users to upload a food image to ascertain if it's good for eating; to implement a KNN algorithm food recommendation system; to apply cognitive sciences to build a diabetes question and answer chatbot; to track user activity and sugar food intakes. The model developed learned features of the images from Ghanaian food dishes with specific nutritional value and essence required for managing diabetics and also provided image classification with given labels and corresponding accuracy. Furthermore, the meal recommender model's performance was tested with a cross-platform user-friendly interface using Cordova and Ionic Frameworks [19] and concluded that KNN performed well in recommending meals to meet the calorific needs of users.

The authors in [20], designed and implemented a food calorie estimation system using the food image. The system can recognize a food image, list the ingredients, and measure the calories before consumption. They utilized ImageAI with RetinaNet feature extraction object detection model to determine food category, and the food image is being captured and segmented into food components while calories are calculated using nutritional fact tables. Food type classification is determined first, then the ingredients are recognized and calories are integrated and calculated for entire food nutrition.

IV. METHOD DESCRIPTION

The two most used methodologies for food recognition to aid the overall well-being of persons with diabetes are discussed here. The two methodologies are CNN and BoF.

A. CNN

A convolution neural network is a multi-layer artificial neural network specially designed to handle two-dimensional input data. CNN is designed to handle image recognition and processing.CNN uses a network structure that mimics a biological neural network, and the model's capacity can be adjusted by changing the depth and breadth of the network and has a strong assumption for natural images (statistical smoothness and local Correlation) [21].

CNN is a feedforward multilayered hierarchical network where each layer performs several transformations using a bank of convolutional layers. The convolution procedure aids in the extraction of valuable characteristics from data points that are spatially connected. A CNN is designed to extract massive complex features of the data at each layer to be able to determine the output correctly. Figure 1 shows a simple CNN architecture with two convolution layers and two pooling layers at the feature extraction level of the network. The classification level constitutes several fully connected classification networks.

A CNN is most suitably used when there is an unstructured dataset (images) and the model needs to extract information from it. Let us take for example, that the task is to predict the label on a food image:

- the CNN receives the food image as an input in a 3D matrix of pixels;
- in the training phase, the hidden layers identify the unique features by obtaining suitable filters that extract information from the images; \
- after the learning network converges, the CNN is then able to provide a prediction regarding the class, an image belongs.

There are up to 22 types of CNN models but listed here are the 9 most popular models for food and image recognition:

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

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a) LeNet: LeNet is the first CNN architecture originally developed to recognize handwritten from 0 - 9 [24]. It comprises seven layers, each with its own set of trainable parameters. It takes a 32 × 32 pixel picture as input. The activation function popularly used is ReLU.
b) ResNet: ResNet is a popular deep learning model and is still widely used to date. The model was announced in the research work in [21]
c) AlexNet: AlexNet is one of the most popular CNN architectures to date proposed for the ImageNet Large Scale Visual Recognition Challenge [25].
d) GoogleNet/InceptionNet: GoogleNet as the name suggests was developed for Google for image recognition. GoogleNet comprises 5 * 5 convolutional layers deep and 27 polling layers. The initial version of GoogleNet known as the InceptionNet is susceptible to overfitting problems [26].
e) MobileNet: MobileNet is a portable architecture that uses depthwise separable convolutions to develop lightweight deep convolutional neural networks. It is effective for an efficient model for mobile and embedded vision applications [27].
f) VGG: The name Visual Geometry group convolutional network was developed by the Department of Science and Engineering at Oxford University. It comprises 16 deep layers applied to the VGG face recognition, and image recognition project [28].
g) Inception V2: Inception V2 is the improved version of GoogleNet/Inception architecture. The two 3×3 convolutions replace the convolutions 5 * 5. The reduction drastically decreases the computational time. Thus, it increases computational speed because a 5×5 convolution is 2.78 more expensive than a 3×3 convolution. Therefore, the implementation of two 3×3 layers instead of 5×5 increases the performance of architecture cites inceptionv2.

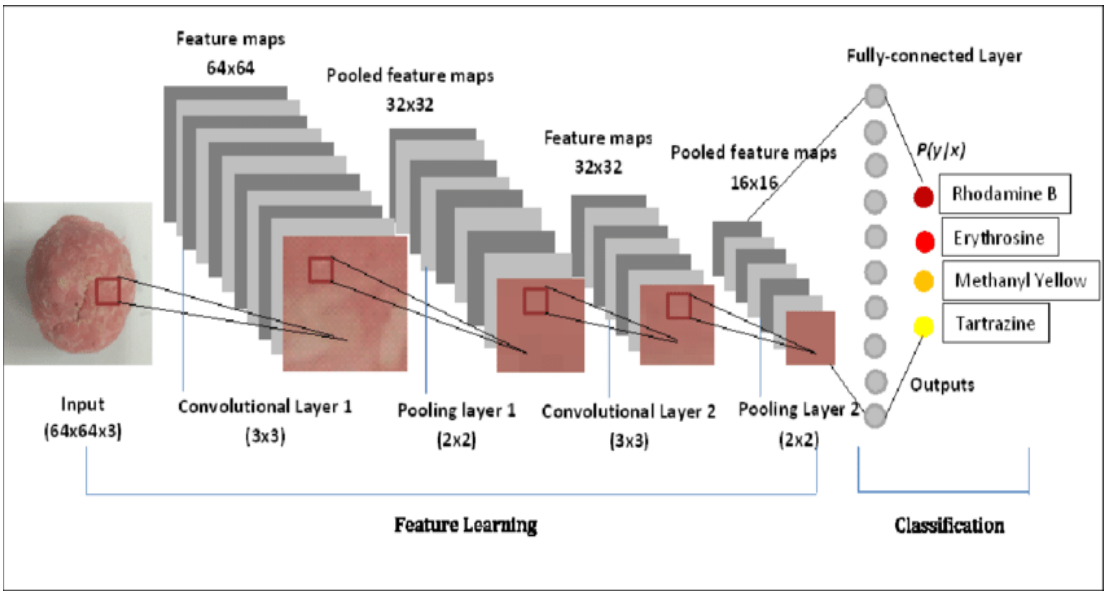

Fig. 1. CNN Architecture [22]

h) Inception V3: Inception V3 was developed by the Visual Geometry group of the Department of Science and Engineering University of Oxford. It comprises 16 deep layers applied to the VGG face recognition, and image recognition project [28].
i) DenseNet: DenseNet is one of the new developments in neural networks for visual object recognition. DenseNet is almost similar to ResNet with some basic differences. ResNet uses an additive method (+) with the future layer, whereas DenseNet concatenates (.) the output of the present layer.

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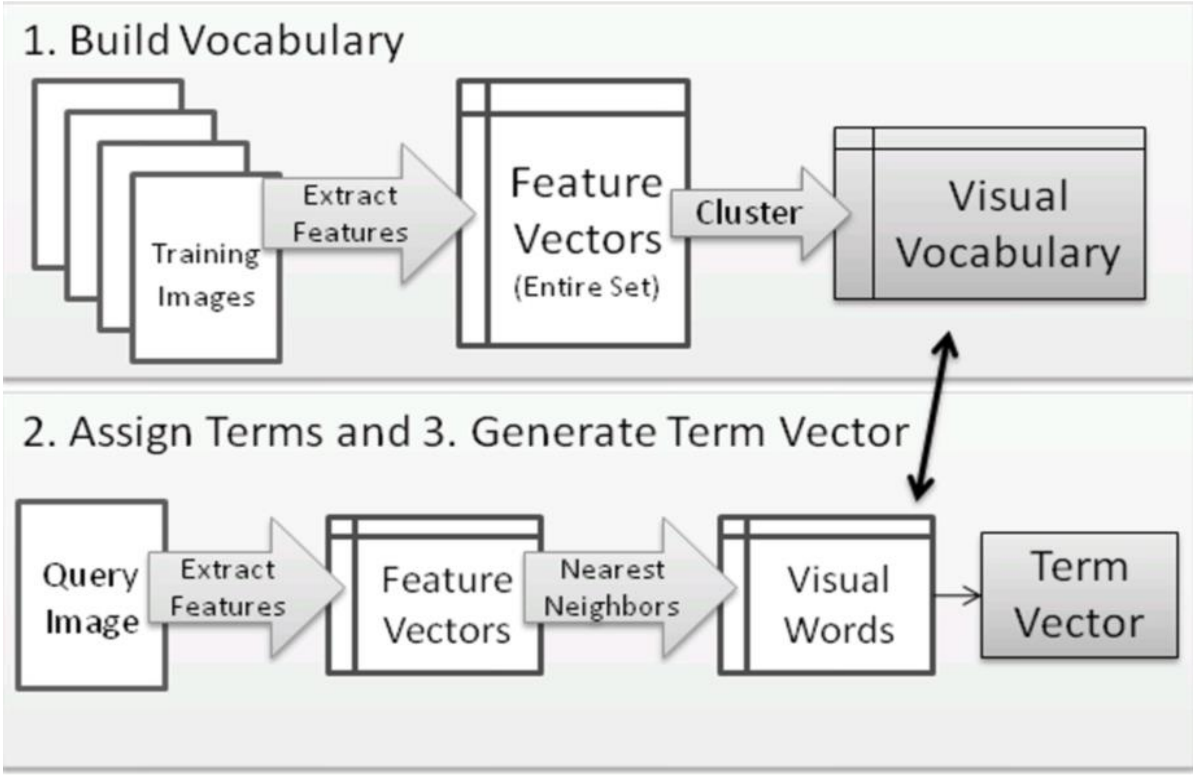

Fig. 2. BoF Image Processing Architecture [23]

B. BoF

BoF is a computer vision model inspired by the bag-of-word model used mostly in Natural Language Processing (NLP). BoF methods are applied to image classification, object detection, image retrieval, and robot visualization and localization [23]. Features from training images are extracted from training and the vectors are quantized to develop a visual codebook [23]. Summarily, Bof can be divided into the following three steps and as shown in Figure 2:

- Feature extraction: At this stage, all the key raw features including the descriptors and the key points are extracted from the images of the training datasets. The extraction can be done with an extraction tool known as Swift [29].
- Codebook generation: In this step, all the descriptors are clustered using a clustering algorithm. It is sometimes referred to as cluster quantization. The image's features are assigned the nearest code in the codebook.
- Feature vector generation: This last step Records the counts of each closest code or term that appears in the image to create a normalized histogram.

V. DATASET

Quality data is the backbone of Computer vision applications. When a dataset is limited, acquiring datasets for CV problems becomes difficult. A custom image or own dataset is the ability to create or build your dataset from scratch. A Real-world problems most times require datasets to be acquired from real-world scenarios. Most food recognition and classification problems entail that real-world dataset are to develop through image segmentation, combing existing publicly available datasets, or building from scratch. There are free and open dataset libraries public, such as COCO datasets. Different geographical regions have different food types, which has widened the research depth on food recognition and classification. Therefore, Table 1 and 2 summarizes the literature reviewed and their corresponding datasets.

VI. RESEARCH GAP

Food recognition and classification to ascertain if the sugar level content is suitable for Diabetic patients' consumption helps to keep track of the sugar level of food diabetic patients eat. The challenges have led to most diabetic persons being culprits of the chronic disease. The current IT-based systems for diabetes patients have shown that existing systems target patients in the developed world. As our languages are different in the same manner, our cuisines are different. Table 1 shows that no research has existed to expand food recognition to aid diabetic people using the food dataset consumed in

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ISO 3297:2007 Certified ⁒ Impact Factor 7.39 ⁒ Vol. 11, Issue 9, September 2022
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third-world countries, for example, Nigeria. Therefore, there exists a gap in the functionalities of the available diabetes applications in the market. None offers food recognition and glycemic index food classifier for diabetes patients in most third-world countries.

TABLE I
SUMMARY OF RELATED WORKS AND DATASETS USED

References	Literature and Dataset		
	Dataset	**Year**	**Food Region**
P Kaur et al.	Foodx-251	2019	Not Specified
Marios M et al	Custom dataset	2014	Eastern Europe
Peter Kamiri	Custom dataset	2016	Kenya
Chang Liu et al.	UEC-100	2017	Japan
Jianing Teng et al.	Custom dataset	2019	China
G.Ciocca et al	Food-475	2020	Europe
Seymanur Aktı et al.	Custom dataset	2022	Middle East
Landu Jiang et al	UEC-FOOD100 and UEC-FOOD256	2020	Asia
M Anitha et al	Custom dataset	2019	Central Europe
Zhidong Shen et al.	Custom dataset	2020	Asian
Seon-Joo Park et al.	Custom dataset	2019	Korea
Yirong and Zhiqiang	VIREO Food-172	2021	China
Ying-Chieh Liu et al.	Food-101, Food-201, Good-3D, and Nfood-3D	2022	Taiwan
Abdulnaser Fakhrou et al.	ImageNet	2021	America
Robert A Sowah et al.	Custom dataset	2020	Ghana
G Kiran Kumar et al.	Custom dataset	2021	Asia

TABLE II
SUMMARY OF METHODS AND TYPE OF RECOGNITION USED IN REVIEWED LITERATURE

References	Method and recognition type		
	Recognition Type	**Year**	**Method**
P Kaur et al.	Recognition	2019	CNN-ResNet
Marios M et al	Recognition and Diabetic dietary assessment	2014	BoF
Peter Kamiri	Recognition and Diabetic dietary assessment	2016	Not defined
Chang Liu et al.	Recognition and dietary assessment	2017	CNN
Jianing Teng et al.	Recognition	2019	CNN
G.Ciocca et al	Recognition and classification	2020	CNN-GoogleNet, Inceptionv3, MobileNet-V2 and ResNet50
Seymanur Aktı et al.	Recognition and dietary assessment	2022	CNN-MobileNet-V2
Landu Jiang et al	Recognition and dietary assessment	2020	CNN
M Anitha et al	Recogniton and diabetic dietary assessment	2019	BoF
Zhidong Shen et al.	Recognition and nutritional assessment	2020	CNN- Inception-v3, Inceptionv4
Seon-Joo Park et al.	Regonition	2019	CNN - AlexNet, GoogleNet, ResNet, VGG
Yirong and Zhiqiang	Food and Ingredient recognition	2021	RLA-Net
Ying-Chieh Liu et al.	Recognition and dietary reporting	2022	CNN- EffientDet
Abdulnaser Fakhrou et al.	Recognition	2021	CNN
Robert A Sowah et al.	Non-food recognition and diabetes management	2020	Tensorflow, KNN
G Kiran Kumar et al.	Recognition and Calorie estimation	2021	CNN-RetinaNet

DOI: 10.17148/IJARCCE.2022.11905

VII. SUMMARY

Food recognition and classification of food sugar content for Diabetic patients helps to keep track of the sugar level of the food they eat. However, from the reviewed related works, none of the systems recognizes and explicitly classify foods based on their sugar level (high and low) content in real-time to aid diabetic patients. Diabetes is a chronic illness requiring patients to be vigilant in monitoring and managing their glycemic fluctuations by carefully selecting what they eat. Patients monitoring their blood sugar levels daily and avoiding food with a high target are essential to managing diabetes. The increasing prevalence of diabetic risk factors and lack of awareness has been the most critical obstacles to overcoming diabetes. The review shows the methods and already existing food datasets and discovered that further research is needed to expand the dataset and explicitly classify foods according to their sugar levels. CNN and BoF are popular image segmentation methods in Computer vision. Favorably, CNN has been the best choice for most researchers because the recognition accuracy of CNN is better than other methods for image Recognition and classification [30].

REFERENCES

[1] Marios M Anthimopoulos et al. “A food recognition system for diabetic patients based on an optimized bagof-features model”. In: IEEE journal of biomedical and health informatics 18.4 (2014), pp. 1261–1271.
[2] World Health Organization et al. Global report on diabetes. World Health Organization, 2016.
[3] Marisa E Hilliard et al. “The emerging diabetes online community”. In: Current diabetes reviews 11.4 (2015), pp. 261–272.
[4] W Miles Cox et al. “Diabetic patients’ alcohol use and quality of life: relationships with prescribed treatment compliance among older males”. In: Alcoholism: Clinical and Experimental Research 20.2 (1996), pp. 327– 331.
[5] Andrey Ignatov et al. “Ai benchmark: Running deep neural networks on android smartphones”. In: Proceedings of the European Conference on Computer Vision (ECCV) Workshops. 2018.
[6] P Kaur et al. “Foodx-251: A dataset for fine-grained food classification. arXiv 2019”. In: arXiv preprint arXiv:1907.06167 ().
[7] Peter Kamiri. “Diabetic E-patient Care System”. PhD thesis. University Of Nairobi, 2016.
[8] Chang Liu et al. “A new deep learning-based food recognition system for dietary assessment on an edge computing service infrastructure”. In: IEEE Transactions on Services Computing 11.2 (2017), pp. 249–261.
[9] Jianing Teng et al. “Recognition of Chinese food using convolutional neural network”. In: Multimedia Tools and Applications 78.9 (2019), pp. 11155–11172.
[10] Gianluigi Ciocca, Paolo Napoletano, and Raimondo Schettini. “CNN-based features for retrieval and classification of food images”. In: Computer Vision and Image Understanding 176 (2020), pp. 70–77.
[11] S¸eymanur Aktı, Marwa Qaraqe, and Hazım Kemal Ekenel. “A Mobile Food Recognition System for Dietary Assessment”. In: arXiv preprint arXiv:2204.09432 (2022).
[12] Landu Jiang et al. “DeepFood: food image analysis and dietary assessment via deep model”. In: IEEE Access 8 (2020), pp. 47477–47489.
[13] M ANITHA et al. “A FOOD RECOGNITION SYSTEM FOR DIABETIC PATIENTS BASED ON AN OPTIMIZED BAG-OF-FEATURES MODEL”. In: (2019).
[14] Zhidong Shen et al. “Machine learning based approach on food recognition and nutrition estimation”. In: Procedia Computer Science 174 (2020), pp. 448–453.
[15] Seon-Joo Park et al. “The development of food image detection and recognition model of Korean food for mobile dietary management”. In: Nutrition research and practice 13.6 (2019), pp. 521–528.
[16] Yirong Xue, Kai Niu, and Zhiqiang He. “RegionLevel Attention Network for Food and Ingredient Joint Recognition”. In: 2021 4th International Conference on Algorithms, Computing and Artificial Intelligence. 2021, pp. 1–6.
[17] Ying-Chieh Liu et al. “Deep-Learning-Assisted MultiDish Food Recognition Application for Dietary Intake Reporting”. In: Electronics 11.10 (2022), p. 1626.
[18] Abdulnaser Fakhrou, Jayakanth Kunhoth, and Somaya Al Maadeed. “Smartphone-based food recognition system using multiple deep CNN models”. In: Multimedia Tools and Applications 80.21 (2021), pp. 33011–33032.
[19] Robert A Sowah et al. “Design and development of diabetes management system using machine learning”. In: International journal of telemedicine and applications 2020 (2020).
[20] G Kiran Kumar et al. “Food Calorie Estimation System Using ImageAI with RetinaNet Feature Extraction”. In: International Conference on Emerging Applications of Information Technology. Springer. 2021, pp. 93–102.
[21] Kaiming He et al. “Deep residual learning for image recognition”. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2016, pp. 770– 778.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 9, September 2022
DOI: 10.17148/IJARCCE.2022.11905

[22] W Pribadi, RE Masithoh, AP Nugroho, et al. "Development of android-based interface to determine color additives in food embedded with convolution neural networks technique". In: IOP Conference Series: Earth and Environmental Science. Vol. 355. 1. IOP Publishing. 2019, p. 012003.
[23] Stephen O'Hara and Bruce A Draper. "Introduction to the bag of features paradigm for image classification and retrieval". In: arXiv preprint arXiv:1101.3354 (2011).
[24] Yann LeCun et al. "LeNet-5, convolutional neural networks". In: URL: http://yann. lecun. com/exdb/lenet 20.5 (2015), p. 14.
[25] Andrew G Howard et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications". In: arXiv preprint arXiv:1704.04861 (2017).
[26] Pedro Ballester and Ricardo Matsumura Araujo. "On the performance of GoogLeNet and AlexNet applied to sketches". In: Thirtieth AAAI conference on artificial intelligence. 2016.
[27] Andrew G Howard et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications". In: arXiv preprint arXiv:1704.04861 (2017).
[28] Zhuang Liu et al. "Learning efficient convolutional networks through network slimming". In: Proceedings of the IEEE international conference on computer vision. 2017, pp. 2736–2744.
[29] David G Lowe. "Distinctive image features from scaleinvariant keypoints". In: International journal of computer vision 60.2 (2004), pp. 91–110.
[30] Sehla Loussaief and Afef Abdelkrim. "Deep learning vs. bag of features in machine learning for image classification". In: 2018 International Conference on Advanced Systems and Electric Technologies (IC ASET). IEEE. 2018, pp. 6–10.