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An Optimized Recurrent Neural Network for re-modernize food dining bowls and estimating food capacity from images

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ABSTRACT

Maintaining health and preventing chronic diseases requires awareness of the energy and nutrient content of one's diet. Due to the rapid development of computing and Artificial intelligence (AI) technology, nutritional evaluation can be performed using smartphones or wearable food images.Thechallenges of this technology include estimating the visual estimation of the amount of food in a bowl. We describe an innovative approach for determining a bowl's dimensions by sticking a paper ruler throughout the bottom and edges yet photographing the outcome. We used a variety of colored liquids, bowls and crystallized foods to evaluate the precision of our technique for measuring food volume employing spherical bowls as boxes. Different food-related datasets can have other numbers of images, types of food dining bowls and estimated food capacity from the images represented. Image preprocessing using a wiener filter enhances the estimating of food dining bowl capacity from images. Following preprocessing, a threshold-based approach to image segmentation is used for the resulting data; finally, we used the Gradient Lion Swarm Optimized Discrete Recurrent Neural Network (GLSO-DRNN) model to present an AI-based multi-dish food identification approach. An excellent mAP = 0.96 was found between the results. The suggested model shows great promise as a means of improving dish reporting because of its high classification performance.The GLSO-DRNN performed better to proving its flexibility and efficient discrete parameter optimization. In addition to offering accurate food quantity estimates, it demonstrated significant potential for other uses in the field of smart dining technology. The results highlight an effective of this advanced computational method that is improving food dining bowls and interactions with components associated with food. In the future, we plan to improve the techniques' performance and incorporate our technology into a working Smartphone based on the cloud environment.

1. Introduction

In nutrition and health studies, image-based nutritional evaluation with a sound device or Smartphone is growing more popular. Every dish in the picture needs to be recognized, as well as its quantity is calculated to measure the amount of energy and nutrients consumed accurately. Predicting meal amounts from images is a complex topic. Numerous methods based on sensors have been developed and documented [1]. Food volume can be measured by using dimension and this is generated on a per-pixel basis by specialized imaging sensors known as a sensor for depth. A second efficient method uses stereo cameras spaced apart by a certain distance. Stereoscopic vision, a process akin to how human eyes perceive depth, estimates food content [2].

Chronic diet-related health issues, such as obesity, hypertension, diabetes and heart disease, are a growing source of concern. Diet education initiatives have been created to raise awareness of the consequences of obesity and to motivate individuals to adopt health-conscious eating practices. Finding out what a person eats at each meal assists in

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avoiding numerous chronic illnesses and offers essential information for managing nutritional issues [3]. To evaluate food and nutrient consumption reliably, a dietary evaluation technique emerges as necessary. In the domains of nutrition and wellness, determining accurate food consumption is considered a potential investigation issue. It would be practical and helpful to use the plate or bowl that the food is served on the weighing standard. The serving size on the scale or bowl is determined beforehand. Whenever the package returns in the photos captured during a nutritional study, the pre-measured data estimates the amount of food or drink inside the package [4].

The Food Frequency Questionnaire is an evaluation of a nutrition instrument that can be used to evaluate how a specific food item is consumed over a particular period, as well as data regarding typical portion sizes. The food frequency survey has emerged as a crucial tool for dietary assessment in studies on epidemiology [5]. A significant health survey is helpful because it provides a valid snapshot of the health of a specific community. The food frequency questionnaire is a fast, simple and cheap alternative to traditional methods of nutritional monitoring. Since smartphones have risen in usage throughout the past decade, a self-reporting Smartphone application have been employed to gather information concerning dietary supplements across a more petite time frame [6]. During as well as following the meal, responders snap photographs of every dish. Numerous smartphone applications involving self-report nutritional evaluation have been developed and created.The study seeks to connect the gap between traditional dining practices and the potential given by the processing of images and visual analysis by re-imagining the classic meal dish as a canvas for technological innovation. Combining these fields can revolutionize eating out by creating an atmosphere that appeals to the taste faculties [7]. The effort aspires to promote an environment of ecologically sound and mindful dining by incorporating nutritional capacity assessments using user-friendly interfaces and mobile applications, thus enabling consumers to make educated decisions regarding their diet and portion sizes [8].The author suggested a method for determining the ideal bowl dimensions and shape by employing a self-adhesive paper strip marked off using ruler increments. A snapshot is taken from using a cell phone or the camera, with a paper measure positioned in the center of the bowl's base and edges. Indicators on the material lose their uniform spacing and the breadth of the stripe fluctuates when viewed from the photograph, both of which provide essential details about the bowl's dimensions and structure [9].Each diner takes food from the serving bowls and places it on a plate or bowl of their own. In the individual eating style, everyone sits at a long or circular table together, despite the fact that each has their own plate of food to finish. While a floral centerpiece is able to be used for solitary eating, it is removed from communal dining settings after the meal starts. In the field of health and nutrition research, image-based nutritional evaluation with a wearable camera or Smartphone has become more popular. Each meal in the image has to be recognized and its volume calculated to precisely track the amount of energy and nutrients are consumed. Numerous sensor-based methods have been documented [29]. Food volume is approximated by using depth, which is produced on a per-pixel level using a specialized image sensor known as a depth sensor.The Food Dining Bowls of technological landscape has advanced significantly in recent years, combining advanced features with contemporary design concepts. To accommodate changing culinary preferences, traditional eating utensils have seen a resurgence that emphasizes both utilitarian and aesthetic appeal. The use of intelligent materials, such temperature-sensitive surfaces and non-slip characteristics, that has gained popularity and improved both user experience with safety [30].Fig. 1 shows the measuring instrument for bowls made of an adhesive paper roll.

Key contributions

- The research provides a practical solution for measuring different spherical bowls by providing a method that entails utilizing a measuring tape positioned symmetrically around the interior and exterior of the bowl.
- The experimentation in this work with various colored substances, bowls and crystallized meals was done to test the accuracy of the suggested strategy and to show how it can be used in a wide variety of datasets involving food.
- To optimize the data received from the preprocessing stage, the study used a threshold-based approach for picture segmentation. A high mAP of 0.96 was achieved after including the GLSO-DRNN model. The proposed system's goal is to promote nutritious eating and to aid in avoiding the development of long-lasting illnesses by making accurate nutritional evaluation tools available to a bigger population.

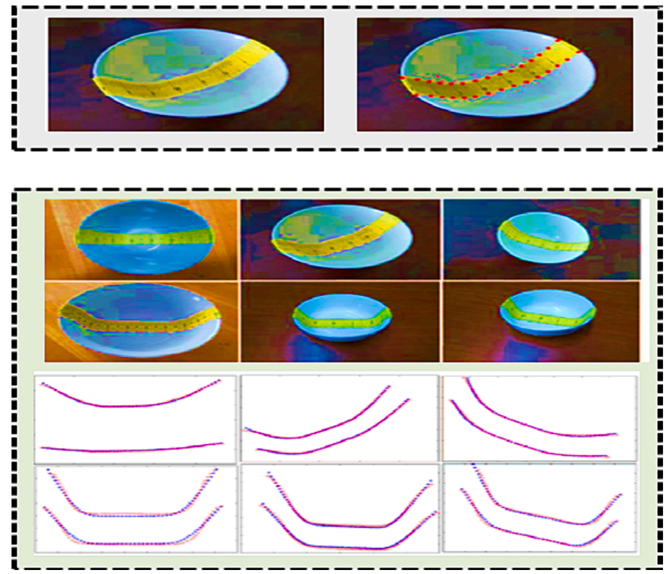

Fig. 1. A ruler-attached bowl ().
Source: https://dl.acm.org/doi/pdf/10.1145/3607828.3617789

In section 2, an extensive exploration of relevant literature is incorporated to inform and contextualize the study. In section 3, a thorough explanation of the methodology is provided. Section 4, a detailed analysis and assessment of the result along with discussion are provided. In section 5, the conclusion's significance is expounded upon through detailed and comprehensive explanations.

2. Related works

The study[10] examined how participants in a buffet-style food entrance rated the nutritional value of their meals, the range of foods available, the quantity of food consumed, the availability of nutritional guidance and the application of nutritional information.The paper [11] focused on reporting the evaluation of the nutritional value compared to discuss plate eating, as well as examining particular variables including human being size of portions along with theutilization compared to discussed plates and the use of technological devices. To better direct subsequent year's efforts to develop in this field.The paper [12] looked at people's ability to calculate the amount of calories in food based on pictures taken from the popular Food-images collection. Sustaining an appropriate weight was dependent on caloric consumption. Experts studying dietary habits and cognitive functions associated with hunger differentiate between foods based on their caloric densities. The paper [13] examined the effects of social and cultural factors on preteens' eating habits. Food and nutrition choices undergo significant changes during the formative years of adolescence. Events involving eating that people do on a daily, weekly, seasonal, or lifetime basis were called habits. The factors influencing people's dietary habits can be gleaned by analyzing their daily activities. The paper [14] assessed the efficacy of a single approach in reducing food waste: modifying dish shape and size in institutional dining facilities. About 31 % of food is wasted between the retail and consumer levels. Young adults were known to be among the most inefficient demographics of customers.The study [15] investigated whether a particular sort of deep learning can improve calorie prediction across different types of Malaysian cuisine. There was a lack of detailed information on Malaysian food and caloric in the existing research regarding food calorie assessment. Thus, the Malaysian diets serve as the basis for collecting data that constitute the basis of the study. The study [16] utilized concepts from the self-signaling as well as determination frameworks to create an empirical framework for investigating the influence of external as well as internal variables on diners' propensity to return to micro-celebrity meals. The trend of eating at restaurants owned by Internet celebrities is rising.The paper [17] assessed the practicability, approval and initial correctness of a 3-day images food record, 1-day foods journal and 1-day measured eating procedure in individuals with SMI. Each participant was assessed twice during four weeks. Normal dietary evaluation procedures can be less workable and accurate for people with serious mental illness (SMI).The study [18] investigated that what happens when this expensive mental process was automated using technology. Calorie information has been shown to have a small to nonexistent impact on food selection when eating out, according to studies. Participants who could add up their calories before placing an order did so less frequently. The paper [19] examined the food's complex qualities; the present study seeks to identify those attributes and determine how they influence customers' perceptions of food's worth yet, in turn, their eating habits for the greater good. The public needs to have a better orientation along with a profound awareness of the worth of food due to phenomena like land overexploitation, food waste, chemical contamination and the use of fast food.The study [20] provided a comprehensive overview of the use of deep learning for identifying foods and assessing their nutritional value in photographs. Maintaining a healthy body, lowering the risk of several diseases and keeping chronic conditions like diabetes and heart disease under control depended on careful management of daily food intake. To ensure a healthy food intake, artificial intelligence has been employed for food picture identification and nutrition analysis.The study [21] investigated how one specific sort of deep learning can improve calorie prediction across different types of Malaysian cuisine. The dietary needs of Malaysians weren't addressed in any of the current investigations of food calorie assessment.The study [22] summarized approaches that can be used for different food category identification operations, including determining the kind, quality,ingredients and quantity of a given food item. For decades, scientists have wondered what would happen if they combined AI with the ability to identify different types of food.The paper [23] focused on deploying an intelligent passive food intake assessment system using egocentric cameras in people's homes in Ghana and Uganda. To reduce the space needed for storing photos, algorithms were developed to eliminate duplicates. The study [24] provided a rough estimate of the caloric content of a food item from a photograph using a combination of Deep Learning and computer vision. The covering was used to calculate the entire surface area of the food items that has been identified. Calories can be estimated by multiplying the food's surface area by the calorie per square inch value. The study [25] focused on incorporating an investigation of nutritional intake, which necessitated precise dietary evaluation. There has been a rise in image-based dietary evaluation applications as an alternative to the more time-consuming and laborious pen-and-paper dietary assessment techniques. Since there haven't been many studies reporting on the reliability of these apps for academic purposes. The study [26] proposed a methodology for estimating food waste at Pierce Dining Hall at Stevens Institute of Technology and outlined steps for putting that methodology into practice. A camera would probably be used in the system and data from a database of different foods would be used to determine the type of food waste. The paper [31] suggested that the most aesthetically acceptable arrangement would be to plate the biggest, calorie-dense part of the meal on the left side of the dishware. Photographs of asymmetrically served poke bowls and their mirror counterpart were shown, and they were asked to choose their favorite arrangement. The most popular poke bowls among the attendees were those with the meal of focal components that are arranged on the left side of the bowl.The study [32] demonstrated that chefs, material scientists, and designers worked together to build a dish for Copenhagen's two-Michelin-starred restaurant ALCHEMIST with an iterative and collaborative method. To developed distinctive eating experiences, they brought together their skills in culinary arts, material behavior, and creative technology. Participants in a playful experiences workshop came up with ideas on to use food ingredients that change form in their recipes. The paper [33] provided the results of two online randomized control experiments to evaluate the efficiency of two menu design strategies for encouraging participants to choose vegetarian meals rather than meat.

3. Materials and methods

The following section offers an in-depth discussion of the proposed multiple-dish food categorization concept. As an initial stage, we collect information regarding the image while running it through the Weiner filter to further develop the concept. Following the images that have been prepared for processing, a threshold-based segmentation technique is utilized. We propose an innovative GLSO-DRNN technique for classifying food volume calculation using spherical bowls as the container. The suggested block diagram is shown in Fig. 2.

3.1. Data collection

In this situation, food photographs are utilized since they are rich in specifics and that is essential for the effectiveness of feature extraction and classification approaches. The detection effectiveness of current techniques and innovative classifications is compared using aggregated big foods image datasets such as UECFOOD-100, UECFOOD-256and Food-101. The amount of photos, the style of food and the types of food contained in a given dataset are a few instances of how these kinds of collections might be differentiated. The UECFOOD-100 dataset, for example, has 100 distinct food categories, each associated with a box of boundaries that specifies the exact placement of each food object in the image. Most food groups in this data collection are staples in the Japanese diet. UECFOOD-256 is identical to UECFOOD-100 that it is a subgroup of that strain. It's different because it features 256 pictures of various foods, rather than the usual 40. There are 101 distinct types of food represented in the 101,000 photos that make up Food-101. Most of the information in several datasets consists of photographs of food scraped from the Internet and shared on social networking sites like Instagram, Flickr and Facebook. Like UECFOOD-100 and UECFOOD-256, Food-101 features Japanese food items. On the list of top 15, Turkish foods are allowed [27]. In addition, the Indian Food Database includes Indian cuisines, while the Pakistani Food Dataset includes Pakistani meals. There are scant data sets that focus on products, such as VegFru, Fruits 360 Dataset and FruitVeg-81. Fig. 3 depicts the software's workflow and displays some example pictures from the nutrient databases.

3.2. Image preprocessing using Wiener filtering

In image processing, the Wiener filter is a well-known method for restoring signals and reducing noise. It is a linear filter that attempts to minimize the average squared difference among the unfiltered and filtering versions of an image. The Wiener filter, used in the context of image preprocessing, can improve images tainted by blurred or noisy additives. As a compromise between inverse filtering and noise smoothing, Wiener filtering is effective. It reverses blurring while canceling out additive noise. The Wiener filter is used to find the

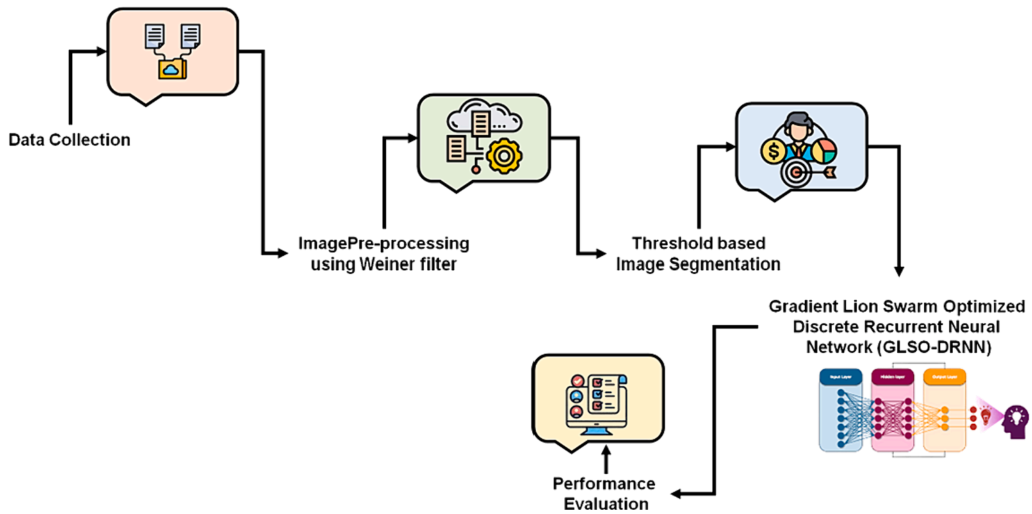

Fig. 2. Suggested block diagram.

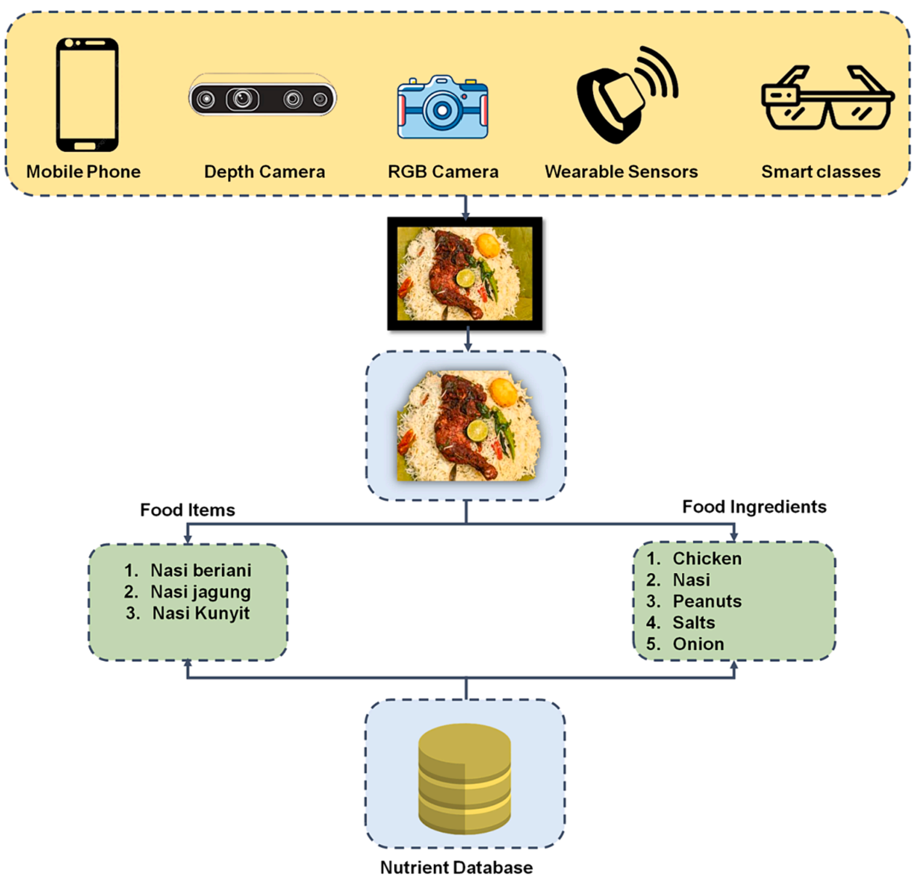

Fig. 3. The System Flow.

procedure that estimate leads to the most minor mean squared deviation from the process of interest. After using inverted filtering and smoothing the noise, it reduces the mean square error to its minimum.

Wiener filtering is a linear approximation of the source image. The primary use of the Wiener filter is to decrease the quantity of noise contained in a snap compared with an assessment of the expected noiseless signal. An empirical method forms the basis of this method. Due to its efficiency and ease of use, the Wiener filter is implemented. Since the ideal filter weights for reducing noise in the signal received are calculated with an ensemble of linear equations, the approach is considered straightforward.A practical estimation of the predictable signal unaffected by Gaussian noise is calculated by estimating the correlations and matrices of covariance of signals with noise. Estimates of the noise statistical data are used to select the ideal combination of filter weights. Following that, the most effective filter weights are applied to an additional input signal containing noise properties comparable to the original movement to determine the stochastic part of the data. This strategy excels when the noise has a Gaussian distribution. In addition, its implementation involves a few computing operations that can be processed efficiently.

$$S(w,c) = \frac{Z^*(w,c)B_g(w,c)}{|Z(w,c)|^2 B_g(w,c) + B_m(w,c)} \quad (1)$$

Using a method of division, B_g simplifies our understanding of its behavior:

$$S(w,c) = \frac{Z^*(w,c)}{|Z(w,c)|^2 + \frac{B_m(w,c)}{B_g(w,c)}} \quad (2)$$

Function of Degradation $= Z(w,c)$
Functions of deterioration that have a complex conjugate $= .Z^*(w,c)$
An analysis of the Noise Power Spectrum $= .B_m(w,c)$
Analyzing the Power of the Spectral Density of the original image $= .B_g(w,c)$

Consider the phrase $\frac{B_m}{B_g}$ represents the inverse relationship between signal strength and background noise. The data obtained based on a pixel's neighboring region, the Wiener filter can be used to clean up a ruined image. The effectiveness of this filter is proportional to the strength of the noise. To explain it differently, the filter smoothes less when the variance is high and smoothesmore the rule is low.The transforms spectrum density is used to find the ideal filter matrix. An additional approach for determining the ideal filter H_0 is to perform a conversion on food capacity estimates derived from image analysis.

$$H_0 = B_{g_0} B^{*S} \quad (3)$$

While specifically used to redefine food eating bowls, h_0 is crucial for assessing the degree to calculating these bowls' capacities based on visual data.

$$h_0 = D_t(D_t + D_m)^{-1} \quad (4)$$

Comparing the matrix move to the reaction time of a linear system, that is referring to as the response matrix. Where d_{min} evaluates a model's performance in locating and recognizing items in images as it involves acomputer vision and object identification.

$$d_{min} = S_u\{D_T D_M (D_T + D_m)^{-1}\} \quad (5)$$

In this particular scenario, obtaining an d_{min} is essential to the effective modernization of food eating bowls since it guarantees the appropriate evaluation of food quantities and improves the overall effectiveness of the image-based estimating procedure.

$$d_{min} = S_u\{D_t D_m (D_t + D_m)^{-1}\} \quad (6)$$

To ensure that the following image segmentation and evaluation operations are performed on more effective, more accurate images, the Wiener filter can be used in embodiment preprocessing during the Food Dining Bowls and Estimating Food Capacity from Images. The Wiener filter can improve the precision of subsequent image processing techniques, allowing for a precise assessment of the food content among the eating bowls by eliminating artifacts and noise from the image. Due to this, it's easier to get a reasonable estimate of how much food is there, which is crucial to completing the effort of calculating food capacities from images.

3.3. Image segmentation using threshold-based image segmentation

Image segmentation is essential for predicting food capacity from photographs when re-designing meal bowls. The basic technique of threshold-based segmentation of images divides a picture into meaningful parts based on intensity or color. The strategy can separate the dining bowl from the food sections, allowing precise meal capacity assessment.

The most elementary approach to image segmentation is called thresholding. Thresholding is a technique for converting grayscale photographs into their binary representations. Segmentation is used to convert color images into binary. To perform segmentation, we divide the original image's pixels into groups. Multiple binary pictures are produced if there are two classes. As shown, thresholding is a technique used in image processing to divide a picture into smaller parts with the help of a single color or grayscale value. Getting a binary image first facilitates recognition and classification because it cuts down on data density.Thresholding takes a grayscale or color image as input. In the simplest form, the segmentation is represented as a binary picture. Pixels with a black backdrop have a white foreground and vice versa. With this technique, the image's pixels are judged by the same predetermined standard. The intensity values of the pixels are used to divide the image.

$$ImageSegmentation = segmentanimageinto(constant)areasorgroupsofpixels$$

$s(y,x) = 1 if l(y,x)$ to be a pixel in the forefront $= 0$ where $l(y,x)$

$$s(y,x) = \begin{cases} 0 l(y,x) < T \\ 1(y,x) => T \end{cases} \quad (7)$$

In practice, graphs contain greater valleys and peaks, finding it hard to determine what number to use for T. The formula for this method is:

$$T = T[y, x, b(y,x), l(y,x)] \quad (8)$$

Where,$l(y,x)$ is a degree of gray and $b(y,x)$ is an area of real estate in the specific area.There are three distinct thresholding techniques in Fig. 4.

Adaptive thresholding involves using varied threshold levels depending on the specific context.

- **Global Thresholding**

When there is a significant brightness difference between foreground items and the backdrop on a global scale, in the global threshold, a single threshold value is used in the full image. For a long time, the gentry hold has been a go-to method. It is possible to employ global thresholding when the component pixel values are consistent with the backdrop pixel values over the entire image.

$$GlobalThresholdin = SetthresholdTtodistinguishanitemfromthebackground$$

$s(y,x)$ Change at the threshold of f(x, y) at a number of global boundariesT

$$s(y,x) = \begin{cases} 1 if l(y,x) \geq D \\ 0 otherwise \end{cases} \quad (9)$$

Global thresholding approaches include optimum, iterative, histogram, clustering, maximum correlation, multi-threshold and multispectral.

- **Adaptive Thresholding**

Global thresholding is unsuitable for irregular background lighting.

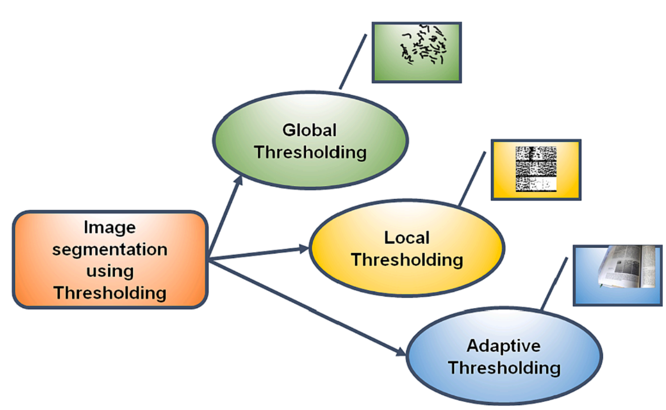

Fig. 4. Three distinct thresholding.

Adaptive thresholding uses a grayscale or image in color as input and returns a binary image for classification. A threshold must be established for each of the pixels in the image.A pixel that follows the threshold has been assigned the foreground value, while those above the threshold are set to the background's quantity. Variable region-specific threshold amounts are utilized in dynamic thresholding. The two approaches assume that lower areas of an image have estimated uniform lighting, making them ideal for thresholding. Adaptive thresholding identifies suitable foreground components from the surrounding pixels based on pixel intensity differences. This strategy is costly instead of ideal applications that operate in real-time. A different method for determining the local threshold is to analyze the intensity values of the local community around each of the pixels statistically. The most effective statistic relies on the supplied image. Employing local thresholding that is adaptive, every single pixel is assigned a threshold according to the brightness values in its vicinity. At the same time, straightforward and rapid functions use the standard deviation of the local concentration distributions. It allows thresholding of images without distinct peaks in the global intensity histogram.

- **Local Thresholding**

Shadows and luminance direction can provide unequal illumination, making a single threshold ineffective. Split the image into m x m sub-images and set a point. Local thresholding works well, provided the gradient effect is minor relative to the sub-picture size. During the regional thresholding approach, the T is determined by the gray levels of $l(y,x)$ and local image attributes, including the mean or variance of surrounding pixels. The threshold function is $D(y,x)$.

$$\mathrm{s}\,(y,x) = \begin{cases} 0 if l(y,x) < T(y,x) \\ 1 if l(y,x) \geq T(y,x) \end{cases} \tag{10}$$

Where $T(y,x)$=$l(y,x)$ + T.

After approximating the gray level histogram to obtain a sub-image utilizing two Gaussian distributions, the threshold is determined by minimizing classification error relative to the point's value. Applying threshold-based image segmentation to re-modernize food dining bowls and estimate food capacity from images can assist in quantifying food content and improve dish communication. This method creates a seamless marriage of technology and food-related design, giving consumers a more engaging and pleasant dining experience.

3.4. Gradient Lion Swarm Optimized Discrete Recurrent Neural Network (GLSO-DRNN)

The Gradient Lion Swarm Optimization (GLSO) algorithm and the Discrete Recurrent Neural Network (DRNN) are two potent optimization approaches that have been combined to create the Gradient Lion Swarm Optimized Discrete Recurrent Neural Network (GLSO-DRNN). This hybrid approach leverages the strong learning capabilities of a discrete recurrent neural network as well as the collective intelligence of a swarm algorithm inspired by lions is to tackle the challenges of sequential data analysis and complex optimization issues.

3.4.1. Optimized Recurrent Neural Network

An RNN's ability to catch sequential information in photos of food bowls allows for precise estimates of their capacities. TheDRNN method can aid in re-modernizing food Dining Bowls as well as Estimating Food Capacity from Images by allowing for a accurate and trustworthy analysis of food content, thereby improving the overall dining experience. Since each user session can be modeled as a series of web page views and DRNN can predict temporal characteristics, its usage in our context for real-time recommendation is painless. While DRNNs with one hidden layer can determine the sequence in which pages were accessed, DRNNs with several hidden layers can distinguish different permutations of page access. The collective hunting behavior of lion swarms, during which the swarm's adaptive mobility and cooperative intelligence ensure effective solutions for space exploration along with exploitation, serves as an inspiration for the GLSO-DRNN system. The global exploration capacity and convergence speed of the GLSO method are improved by the efficient search for optimal solutions is made possible by integrating this adaptable technique throughout the optimization process.DRNNs can analyze time-ordered data. In this research, we focus on the discrete RNN, which divides the process into several states, each associated with a specific point in time. The fundamental idea behind DRNN is demonstrated. Let's pretend u and bis the input and output, respectively. It's what we use to symbolize deep-level information.

There are three transit matrices: $\mathrm{C}, \mathrm{W}, and \mathrm{Y}$. Since the hidden layer has a self-link, the values will shift over time. For a more thorough explanation, consider the DRNN as a whole network. Assume that there are three possible states in a given $\mathrm{g}\,-1 and \mathrm{g}\,+1.\mathrm{u}(i) and \mathrm{b}(i)(d-1 \leq g \leq)$ $\mathrm{g}+1$ display input and output in many formats.The state values hidden behind the surface ,$p(i-1)$, depend on which the variables are $p(i-1)$. Weight carried over from the previous state. Initially, we have:

$$p(i) = d(Cu(i) + \mathrm{Y}p(i-1)) \tag{11}$$

Functions of nonlinear learning, such as tanh, ReLU and F, stand for the larynx as well as the sigmoid.State-level forecasting i is $b(i)$ and the equation is as follows:

$$\mathrm{q}(i) = softmax(\mathrm{W}p(i)) \tag{12}$$

Therefore, an output can be obtained at any moment. Interestingly, the transit matrices remain identical even though the network has been unfolded ,$WandY$. TheDRNN involves the same set of calculations. The time and effort required to calculate the DRNN is reduced.

- **Infinite States RNN Model**

The input to our scenario is a list of URLs in the format g $\{\mathrm{q}_0, \mathrm{q}_1, \cdots, \mathrm{q}_{\mathrm{n}-1}\}$, an instance of a user browsing across pages q_0 before $q_{\mathrm{g}+1}$. A distinct aspect of the journey is detailed on each page a user navigates. To simulate the actions of the web shop's customers, the DRNN is transformed into a state machine. With infinity storage facilities, the DRNNcan simulate any potential situation. The input layer of our DRNN is N-state. Each icon stands for a separate frequently-seen website. We develop a N-N-element vector W_g for each page $\mathrm{p}(t)$. $W_g[\mathrm{Q}_s]$ is 1 and the sum of other factors is zero. During the g + 1 condition at the input layer, it's a type of vector W_g that provides the input. ADRNN contains K hidden levels for every single state that stands for every neuron in each of these levels. The web store features n pages with m products. The initial amount of a will be between and $M''L''N$. It is important to remain in mind that the number of neurons in a layer might vary from layer to layer.

To begin, the developers take a simple approach and assume that each layer contains the same amount of neurons. Throughout a state, the neurons of i^{th} layers can communicate with one another $i+1$ layer. The i^{th} layers of state t neurons are in constant two-way communication with the i^{th} layer of state $d+1$. The network's last layer's probability vector is $\mathrm{W}_{out}\{w_0, w_1, \cdots, w_{M-1}\}, u_s$. Possibilityof the i^{th} variable represent $st+1$ g the ith item. For instance, a probability of 0.5 exists that the initial item will be obtained today. There is one final hidden layer that links to the state's output layers. When a system transitions to a new state, we can predict its future behavior. We hypothesize that the suggested system will direct customers to the R items that they are most likely to buy.

The state of the ith layer at instant t is represented by $\mathrm{p}_i(\mathrm{g})$ using the following update function:

$$p_i(g) = \begin{cases} f(Y_{ipi}(\mathrm{g}-1) + x_i(p_i - 1(g) + e_i(g)))jli > 1 \\ f(Y_{ipi}((g-1)) + x_i(\mathrm{W}_i + \theta(\mathrm{q_g})))jli > 1 \end{cases} \tag{13}$$

The function provides a time-stamped notation for link weights g −1 and x_i weights of the connections in the initial hidden layer as y_j. A symbol of bias is $e_i(g)$, while the amount of time spent on a page is indicated by $thee_i(g)$ layer of input. A network's topology is indicated by q_g. There are three parallel dimensions and three secret levels. At its most simple level, it logs the dates and times in which a user accesses each website. The achieving success layer simulates the process of visiting two websites one after the other. The fthlayersummarizes the information found in the f −1 online pages that can be seen in any sequence.Recurrent Neural Networks are used in the framework to estimate food capacity from photos and re-design food-eating bowls, allowing the system to record dynamic changes in the food presentation as well as temporal relationships. RNNs help to make more precise and flexible estimations of food capacity by utilizing the sequential nature of the visual input, which improves the efficacy and precision of the eating experience.

3.4.2. Gradient Lion Swarm Optimized (GLSO)

Inspired by a lion shooting operation, researchers developed the ground-breaking swarming intelligent optimizing approach known as GLSO. The alpha female and her cubs are the most important factors in their calculations. The essential idea behind this approach is that the two lionesses should work together to find the optimal dominance objective by matching the conditions that provide the highest values for the functionality objectives. In each cycle, the lone lions-king of the animal herd occupies the prime hunting grounds. When they are young, lion pups follow the mother lion while she hunts or eats. At maturity, a lion cub is separated from the pride and released close to its former feeding grounds. The optimal attributes of the objective functions are identified via the lion team's constant investigation.

The algorithm's essential operations are as follows:

Step 1: Initiate the current situation. The GLSO objective function l (x), the total number of lions in a gathering N, the ratio of individual lions to the total number of lions, the optimal division length z and the maximum possible number of permutations W,in addition to the location $x_i = (x_i1, x_i2, \cdots, x_iz)$ of the ith one of the criteria of the structure is the number of lions in a large swarm. Each lion has been placed in the spot that has served as the greatest home base for it during its entire history.

Step 2: To adjust the placements of the lion-king, lionesses and Lions club, we utilize formulas (10), (11) and (12) correspondingly.

$o \le \frac{1}{3}$ According to equation (12), the lion babies eat quite near to their mother.

$\frac{1}{3} < o \le \frac{2}{3}$ proves that adult females and cubs hunt together.

$\frac{2}{3} < o \le 1$ Occurs, the young cubs are separated from the throng.

Components of equations (10) and (12), their definitions and the methods are used to determine individuals.

$$U_i^{f+1} = z^f(1 + \gamma\|q_i^f - z^f\|) \tag{14}$$

$$U_i^{f+1} = \frac{q_i^f + q_t^f}{2}(1 + \propto_j \gamma) \tag{15}$$

$$U_i^{f+1} = \begin{cases} \frac{z^f + q_i^f}{2}((1 + \propto_v \gamma)k \le \frac{1}{3} \\ \frac{q_m^f + q_i^f}{2}((1 + \propto_v \gamma)\frac{1}{3} < k \le \frac{2}{3} \\ \frac{h^{-l} + q_i^f}{2}(1 + \propto_v \gamma)\frac{2}{3} < k \le 1 \end{cases} \tag{16}$$

Step 3: Calculate the objective functional score. Change the optimal settings from before p_j^k from each separate lion, as well as s^r of the animal group, using the updated coordinates for each lion obtained in phase 2 from the target variable.

Step 4: The location of the lion king is reevaluated. During five cycles, the position of the lion-ruler is revised based on the outcomes of the preferred parameter. The final result is the lion-ruler's location, which means that the target function has been approached under its terminal conditions. If not, move to step 2.

The GLSO-DRNN architecture and the GLSO algorithm work together seamlessly to provide a viable solution for a variety of applications that require complicated optimization and sequential data analysis. This new hybrid technique has the potential to lead better learning capacities, better optimization performance and precise predictions, which will progress approaches for analysis and optimization across a range of fields.Algorithm 1 using the process of GLSO-DRNN.

Algorithm 1. (*Process of GLSO-DRNN*) **Step 1:** Set the GLSO-DRNN model's initial values.

- Count the number of hidden pieces in the recurring layer
- Select a learning speed
- Define how many times the optimization procedure will repeat

Step 2: Initialize the lion swarm population

- Create the first known population of lions

Step 3: Define the DRNN architecture.

- Assign the proper dimensions to the input layer for the data on renewable energy.
- Give the input layer for the renewable energy data the appropriate dimensions.
- Build the output layer using the right dimensions for the forecast

Step 4: Training the GLSO-DRNN model.

- Continue for the predetermined number of times
- For every lion present in the population
- Provide the DRNN with historical statistics on renewable energy
- Determine the discrepancy between the actual and projected outputs
- Use the Lion Swarm Algorithm to update the lion's location inside the swarm
- Using the updated lion positions as a basis, update the DRNN settings

Step 5: Prediction using the trained GLSO-DRNN model.

- Feed a fresh set of input data on renewable energy into the trained RNN
- Obtain the predicted output

Step 6: The GLSO-DRNN model should be analyzed for its efficacy.

- Check the expected and actual results for the dataset used for testing
- Compute the metrics for forecast accuracy

Step 7: If additional epochs are required for optimization and improvement, repeat steps 4 through 6 many times.

4. Results and discussion

Real-time applications need more efficient processing times from the developed approach, so it could be used in conjunction with other components like an application for mobile devices and a server to accomplish the food identification function. To prepare the images for analysis, we used the measurement tools in MATLAB. Our model provides accuracy and precision in the given hyper-parameter configuration, while Single-Shot Detector (SSD), R-CNNand EDD1-ENB1 are limited to achieve optimal performance. As can be seen from the table's outcome, our model identified dishes under the classifications with more accuracy than the other existing methods.Our model identified the food items with a mAP. The total mAP performance throughout all rounds matched the results we saw for recall, accuracy, precision, and F1-Score. As a result, these existing approaches were chosen to be compared to our suggested model. We employed the proportion used to evaluate the effectiveness of the proposed model. This is a frequently used statistic for models that identify or recognize images. Three parameters might be obtained from this measurement: false negative (FN), true positive (TP) and false positive (FP). We computed four fundamental metrics: accuracy, precision, recall and F1-score based on these variables. Accuracy, F1-score, recall, precision and mAP were the criteria for selecting the performance comparison elements. During every training round, a comparison was made.

4.1. Accuracy

A significant level of accuracy in food capacity estimation improves customer satisfaction and adds to system performance and overall dependability, making it a useful tool for streamlining and streamlining food-related procedures. The result of insufficient accuracy is the difference between the result and the actual number. The proportion of actual outcomes demonstrates how evenly distributed the data are globally. Equation (13) is used to evaluate accuracy.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

Fig. 5 and Table 1 display the comparable values of the accuracy measurements. In contrast to the employed techniques, SSD, R-CNN and EDD1-ENB1 exhibit accuracy rates of 53 %, 54 % and 87 %, respectively. With an exceptional accuracy of 96 %, the suggested method, Integrated GLSO-DRNN, is effective. This method outperforms the others in terms of performance.

4.2. Precision

Attaining precision in the present manner denotes the system's capacity to recognize minute characteristics in the images and provide consistently reliable judgments of meal amount, improving the overall effectiveness and dependability to update an eating experiences.The ratio of categorized incidents to the total number of cases with accurate information constitutes the definition of precision and it is an essential part of accuracy. To calculate the precision, use equation (14).

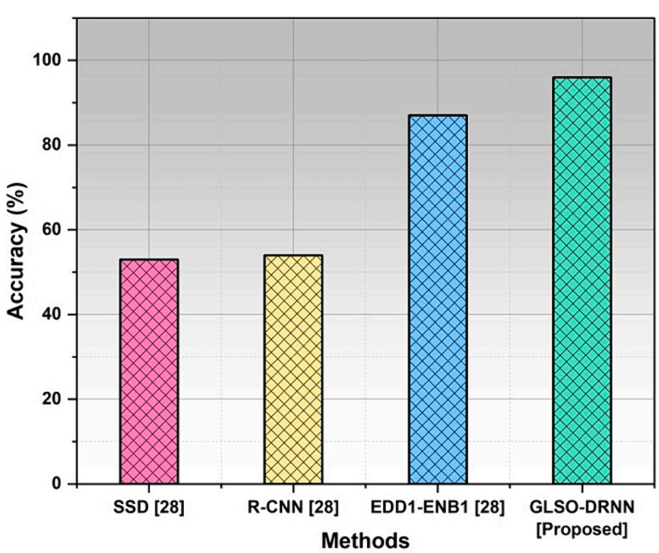

Fig. 5. Numerical Outcomes of Accuracy.

Table 1
Comparison of accuracy for proposed and existing method.

Methods	Accuracy (%)
SSD [28]	53
R-CNN [28]	54
EDD1-ENB1 [28]	87
GLSO-DRNN [Proposed]	96

$$\text{Precision} = \frac{TP}{TP + FP} \tag{18}$$

The recognizing rates of SSD, R-CNN and EDD1-ENB1 are 60 %, 64 % and 88 %. The impressive 94 % accuracy rate of the suggested technology GLSO-DRNN is special. Fig. 6 and Table 2 show that this method is superior to an existing plan.

4.3. Recall

The recall highlights the system's ability to extract relevant information and insights that are essential for effectively reconsidering the dynamics of portion estimate and food presentation in a contemporary culinary setting.The recall rate measures how a model can identify each outlier in the same data set. One quantitative definition is the proportion of correct diagnoses relative to the combined percentage of accurate diagnoses and false negatives. The recall (15) can be determined with an equation.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{19}$$

Fig. 7 and Table 3 provide the corresponding recall measurement comparison data. The SSD, R-CNN and EDD1-ENB1 had above-average recall rates of 56 %, 53 % and 93 %. With aGLSO-DRNN recall of 95 %, the suggested method outperformed the state-of-the-art.

4.4. F1-score

A high F1-score indicates that the model successfully strikes a balance between preventing misclassifications and precisely determining food capability from images in the overall setting of this creative approach to modernizing dining bowls, ultimately enhancing the accuracy and dependability of the system.The accuracy and recall components of the F1-score are used to measure a model's performance in binary classification tasks. The model's accuracy is calculated using a single number considering both measures. In the proposed method,

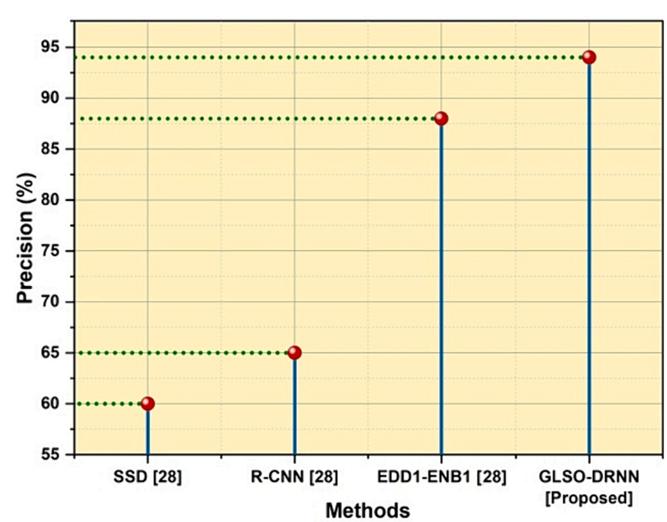

Fig. 6. Numerical Outcomes of Precision.

Table 2
Evaluation of Precision for proposed and existing method.

Methods	Precision (%)
SSD [28]	60
R-CNN [28]	64
EDD1-ENB1 [28]	88
GLSO-DRNN [Proposed]	94

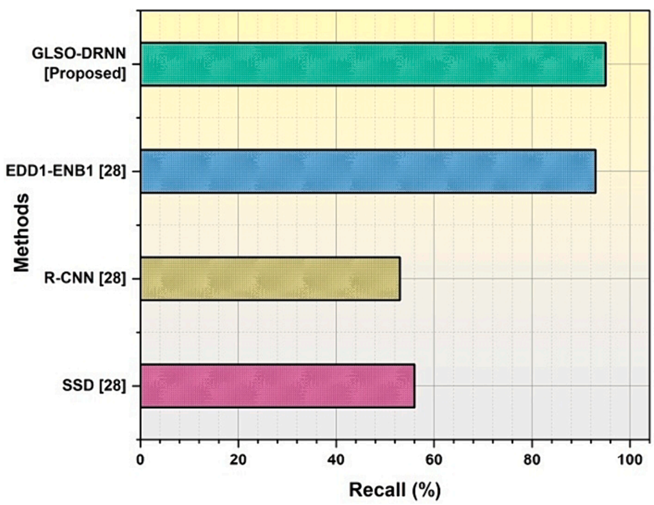

Fig. 7. Numerical Outcomes of Recall.

Table 3
Comparison of Recall for proposed and existing method.

Methods	Recall (%)
SSD [28]	56
R-CNN [28]	53
EDD1-ENB1 [28]	93
GLSO-DRNN [Proposed]	95

recall and precision are merged into a single statistic called the f1-score. Our suggested technique achieves 56 %, while current methods like SSDas well asR-CNN manage 57 % and EDD1-ENB1 manages 93 % in this comparison. It proves that our proposed method is superior to the status quo. Fig. 8 and Table 4 depict the comparative study of the proposed and current systems.

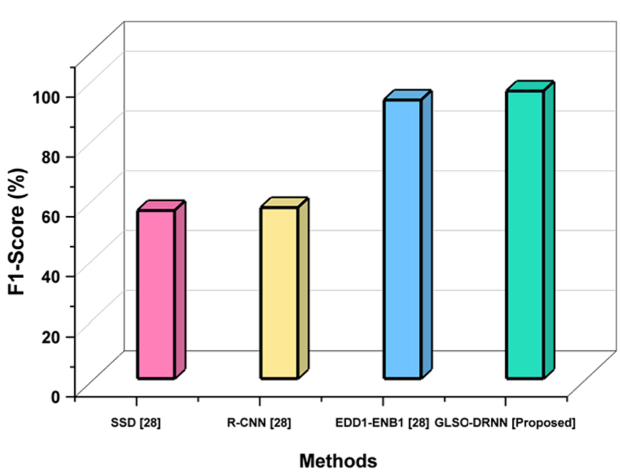

Fig. 8. Numerical Outcomes of F1-Score.

Table 4
Comparison of F1-Score for proposed and existing method.

Methods	F1-Score (%)
SSD [28]	56
R-CNN [28]	57
EDD1-ENB1 [28]	93
GLSO-DRNN [Proposed]	96

$$\text{F1} - \text{score} = \frac{(\text{recall}) \times (\text{precision}) \times 2}{\text{recall} + \text{precision}} \tag{20}$$

4.5. Mean average precision (mAP)

mAP offers a comprehensive evaluation of the model's performance by calculating the mean and calculating the average precision across many categories. This ensures that the updated eating experience is consistent with dependable and accurate food capacity predictions obtained by image analysis.The overall result was calculated using the mAP, which can be interpreted to represent the precision-recall gradient, provided the input and output threshold has been set to a value of and the AP is calculated across every category. Using mAP throughout the training rounds, we compared the model's predictions to the ground reality regarding how the bounding boxes localized and categorized the dishes; with a mAP = 0.96, our model identified the foods, as shown in Fig. 9 and Table 5.In terms of accuracy, precision, recall and F1-Score, their results were identical.

The results were more difficult when using SSD (mAP = 0.57), followed by faster R-CNN (mAP = 0.64) and EDD1-ENB1 (mAP = 0.90). R-CNN, SSD and EDD1-ENB1 were shown to be insufficient for observing several dishes.

4.6. Discussion

The estimation of food volume, bowl reconstruction and, in the end, nutritional intake is the topics of several significant discussions in this section.The methodology proposed in this study can be used to identify different food kinds in households, restaurants and school cafeterias, including multiple-dish meals and mixed-single foods. In many food reporting situations, it was typical to see several dishes on a plate or dish. There was a great deal of food reporting. The recognition of multiple-dish images was supported by the image recognition applications that were already in use. To identify and recognize many dishes from a single image, a statement strategy was desired. For medical

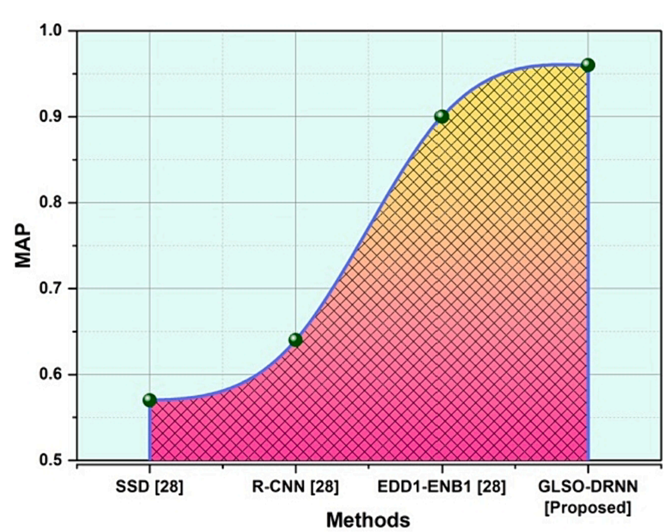

Fig. 9. Outcomes of mAP.

Table 5
Comparison of mAP for proposed and existing method.

Methods	mAP
SSD [28]	0.57
R-CNN [28]	0.64
EDD1-ENB1 [28]	0.90
GLSO-DRNN [Proposed]	0.96

purposes, calculating calories serves as a critical sub-function for wellness self-administration through precise and on-time consumption of food. The performance of the suggested model, its possible uses and its limitations are discussed in the following. The outstanding performance of our proposed Integrated GLSO-DRNN model according to the criteria for assessment, demonstrates its superiority over current approaches in recognizing and identifying images.

5. Conclusion

The amount of food consumed cannot be accurately and consistently determined from photographs, despite diet's significant role in preserving human health as well as preventing chronic diseases. The inability to measure a bowl, a typical food container in the two-dimensional picture space with a sufficient degree of accuracy presents one of the difficulties. Sustaining a healthy way of life and averting chronic illnesses require a thorough comprehension of the energy and nutritional makeup of one's food. Food photos taken with a Smartphone or wearable device can be used to evaluate nutrition due to developments in AI and computer technology. There are a few difficulties in estimating the amount of food in a bowl based on an image. As a result, we introduced a GLSO-DRNN for image classification. Performance metrics like accuracy (96 %), F1-score (96 %), precision (94 %), recall (95 %), as well as mAP (0.96), are measured against conventional technology and ranked like the SSD, R-CNN and Oriented EDD1-ENB1. The findings illustrate the effectiveness and precision of the proposed model in food volume estimate and classification, indicating its potential to enhance dish reporting. In the future, the research intends to improve the effectiveness of the used algorithms and incorporate the created system into a functional, real-world mobile and cloud-based platform. This integration would promote healthier lifestyles and help prevent chronic diseases by providing universal access to precise and dependable nutritional evaluation tools.Different food textures, bowl shapes, and lighting conditions are affected accurately that meal volume is estimated. Widespread adoption is hampered by user adjustment to technologically sophisticated dining utensils and associated with cost concerns. The incorporation of interactive elements or sensors provides result in durability and maintenance difficulties.Future research in this developing field will focus on creating user-friendly tools and applications for widespread use as well as investigating machine learning techniques for continual enhancements in the accuracy of food capacity estimations.

CRediT authorship contribution statement

Veena N.: Writing – original draft, Data curation, Conceptualization. **M. Prasad:** Writing – review & editing, Investigation, Formal analysis. **S. Aruna Deepthi:** Writing – review & editing, Resources, Methodology. **B. Swaroopa Rani:** Writing – original draft, Validation, Resources. **Manjushree Nayak:** Writing – original draft, Visualization, Software, Data curation. **Siddi Someshwar:** Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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