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SOOTYDEEPFIC: Food Item Classification Using Sooty Tern optimized Deep Learning Network

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Abstract: Foods can be categorized based on their chemical composition, purpose, necessity, concentration, and nutritional value. Protein, fat, and carbohydrates are all categorized as caloric nutrients because they provide the body with the energy it needs to function. In this paper proposed a novel deep learning-based food items classification (SOOTYDEEPFIC) method to classify the variety of food items from the dataset with their calorie values (CV). In the first, the sigmoid stretching methods the images are processed utilized to increase the image quality and remove the noises. Consequently, the segmented images are pre-processed utilizing U-net algorithm. The extracted features are then normalized utilized the sooty tern optimization algorithm (STOA). Food items are classified using Ghostnet based on these relevant features. The experimental result shows the proposed SOOTYDEEPFIC yields an overall accuracy is 99.89%. As compared to existing methods, the proposed SOOTYDEEPFIC shows better results in terms of Accuracy. The Proposed approach enhance the overall accuracy of the proposed SOOTYDEEPFIC, F-RCNN, AFN, and DL applications used to classify fruit images is 99%, 98.8%, 98% and 97 % respectively.

Keywords: Deep learning, Sooty tern optimization algorithm.

1. Introduction

Obesity and overweight pose a health risk since they are abnormal fat accumulations. [1, 2] Obesity and overweight can cause a variety of health issues, such as type 2 diabetes, high blood pressure, stroke, heart disease, liver disease, gallstones, joint issues, certain malignancies, as well as other disorders including sleep and breathing difficulties. [3 ,4]. Obesity has a detrimental effect on almost every element of health, including life expectancy, risk of chronic illnesses like diabetes and cardiovascular disease, influence on breathing, mood, and social interactions, as well as sexual function. Obesity is not always a permanent issue.

A calorie is an energy unit based on the outmoded idea of heat. His two primary definitions of "calorie" are commonly utilized for historical reasons [5, 6]. The amount of heat necessary to enhance the temp of 1 kilo of water by 1 degree Celsius (1 Kelvin) was initially characterized as bulk calories, dietary calories, food calories, or kilogram calories [7, 8]. Microcalories, also known as gram calories, are the quantity of heat needed to grow 1 gram of water by the same amount. As a result, 1000 little calories are equivalent to 1 large calorie [9, 10]. A calorie may be thought of as a measurement of energy. Calories are frequently used to determine the amount of energy in meals and beverages [11]. You must consume less calories each day than your body uses in order to lose weight. To gain weight, you must consume more calories than you burn.

Furthermore, present approaches have a number of shortcomings, including low accuracy, substantial variance in calorie content, and incorrect values generated during calorie measurement owing to

Table 1. List of Notations

Notation	Description
H (v, u)	enhance pixel value
fs (v, u)	original image
t	threshold value
b	contrast factor
$y_p^{g(l,m)}$ and $y_p^{r(l,m)}(t-1)$	convolutional layers
$(w_h^g)^T$ and $(w_n^r)^T$	weight of the convolutional layers
y1k1	CNN unit's output
R_ and	random number
C_{ij}	search agent
S_{radius}	radius of each spiral round
$V_{ij}(p)$	updates the positions of other SA
$g' \in T^{e*k*k*n}$	filter
$k \times k$	convolutional kernel size
n	intrinsic feature maps
$X_1 \in T^{h'*w'*m}$, $w'$and h'	feature maps breadth and height
m	number of ghost feature maps

misclassification [12, 13]. To address this issue, a unique deep learning-based food classification strategy (SOOTYDEEPFIC) was suggested, which classifies various meals in a dataset based on their CV. The following are the primary contributions of the suggested method:

- First, the image is processed using the sigmoid stretching method to improve the image quality and remove noise.
- U-net algorithm is segmented using pre-processed images
- Sooty Tern algorithm is extracted the features are then normalized.
- Based on relevant features the Ghostnet is used to classify the food items.

The remaining portion of the work has been followed by, Section 1 illustrates the Introduction of the proposed SOOTYDEEPFIC and Section 2 illustrates the Literature Survey of the work, Section 3 illustrates the Proposed Methodology, Section 4 illustrates the Result and Discussion of the work and finally the section 5 illustrates the Conclusion of the proposed SOOTYDEEPFIC.

2. Literature review

Food images are visual representations of food made up of either tangible or intangible elements. Food image processing algorithms based on deep learning are discussed in this section.

In 2019 Wasif et al., [14] suggested a faster RCNN (F-RCNN) be utilized to identify and get a cutting method for segmentation and feature extraction (FE). Then, using the probing item, determine the known volume and measure the volume of the meal. The calorie content of food is calculated using volume, although this technique is fairly complicated.

In 2023, He, J. and Zhu, F., [15] suggested a per-epoch instance booster with a dynamic threshold that rises over training rounds. The classifier is then cosine normalized to provide a scale-invariant output, which is then integrated with a new loss function to enhance within-class compactness and inter-class discrepancy. Despite the fact that we concentrate on food photographs, our technique is tested on three benchmark datasets, including his two food image datasets. Our solution outperforms all others, and the ablation investigation supports each component of the proposed method.

In 2022 Shahi, T.B., et al., [16] suggested a lightweight deep learning model based on a pre-trained MobileNetV2 model and an attention module. The evaluation of our suggested technique utilizing a transfer learning methodology on three public fruit-related benchmark datasets reveals that our suggested method has a minimal number of trainable parameters and excellent classification accuracy on four of them. It has been found to outperform cutting-edge deep learning algorithms.

In 2022 Gill, H.S. and Khehra, B.S., et al., [17] proposed a Deep Learning application for fruit image categorization. CNN is used to find the best characteristics. RNN is used to label features. The LSTM algorithm is used to deal with exploding and disappearing gradients that arise during RNN marking. The best characteristics retrieved and labeled by CNN and RNN are used by LSTM to classify fruits. Extensive trials on fruit photos were carried out utilizing the suggested technology as well as current competing technologies. The classification rate is unaffected by increasing the dataset from 40% to 50%, 50% to 60%, and 60% to 70% throughout the classification process.

In 2022 Jiang, L., et al., [18] proposed a present a three-step technique for recognizing multi-element (food) pictures, beginning with discovering suitable areas and ending with object classification using deep convolutional neural networks (CNN). Experiment findings demonstrate that our system can detect meals reliably and effectively provide nutritional evaluation reports. This provides consumers with a clear understanding of healthy eating and assists them in developing a daily regimen to improve their health and well-being.

In 2023 Han, Y., et al., [19] proposed a ClusDiff, a clustering-based conditional training framework, is proposed to solve the difficulty of high intraclass variation in food datasets. This methodology enables you to build more diverse and representative food pictures that are more indicative of the underlying distribution of your training data. The experimental findings reveal that our proposed strategy outperforms the baseline diffusion model in terms of enhancing food picture production.

In 2023 Mansouri, M., et al., [20] proposed a MFOOD-32 is a food identification dataset that comprises 32 food types consumed by Moroccans as well as 6400 photos acquired from the internet and other existing datasets. His three pre-trained CNN models are used to analyze the dataset: MobileNet, DenseNet, and EfficientNet. The assessment performance was encouraging, with up to 98% classification accuracy.

2.1 Review on optimization

Introducing a new optimization algorithm called puzzle optimization algorithm (POA) [21] to solve various optimization problems. The main idea in the design of the proposed POA is the mathematical simulation of the process of solving a puzzle as an evolutionary optimizer. The various steps of POA are explained and then its mathematical model is presented. The main advantage and feature of the proposed POA is that it has no control parameters and therefore does not require parameter setting. The performance of the proposed POA is tested on twenty-three different objective functions. In addition, the simulation results show that the proposed POA is far better and much more competitive than the eight compared optimization algorithms.

A stochastic Komodo algorithm was developed which is derived from the behavior of Komodo during foraging and mating calls [22]. Three different Komodo species make up this algorithm: big male, female, and little male. While female Komodos carry out diversification based on the search space radius, males concentrate on intensification. At the start of the iteration, the sorting mechanism is removed and a random distribution of the Komodo is undertaken. This algorithm is very competitive in both unimodal and multimodal functions, yet it can add a more comprehensive evaluation.

presents a new metaheuristic: extended stochastic coati optimizer (ESCO) [23]. ESCO is developed by expanding the shortcoming coati optimization algorithm (COA). ESCO expands the number of searches and references used in COA. ESCO also implements a stochastic process for each unit to choose the searches that will perform. It differs from COA, which splits the population into two fixed groups, each performing its strategy. ESCO implements three sequential phases in every iteration. Through investigation, the multiple search approach is more effective than the single search approach.

A guided pelican algorithm was developed for the enhancement of the pelican optimization algorithm (POA) that replicates the hunting behavior of pelican birds [24]. The global best solution is used by GPA as a deterministic target in the beginning, replacing the randomized target. In addition, when calculating local search space size, GPA swaps out the pelican's present location for the size of the search space. Thirdly, GPA uses numerous candidates in both phases, as it did in the original POA. This algorithm efficiently solves the portfolio optimization problem. Yet this implementing algorithm in real-time is challenging.

offered a new swarm-based metaheuristic called as walk-spread algorithm (WSA) [25]. WSA is a metaphor-free metaheuristic as it does not use any metaphors and adopts its core strategy (walk and spread) as its name. It consists of four searches that are performed sequentially. Through assessment, WSA is proven superior compared to the five new metaheuristics as its confronters. Moreover, WSA is proven fast due to its superior achievement taken in the low maximum iteration circumstance. In the higher maximum iteration, WSA can find the global optimal solution of ten functions.

presented the description and investigation of the designed metaheuristic called as four-directed-search algorithm (FDSA) [26]. FDSA is a metaheuristic that performs multiple directed searches and does not conduct neighborhood searches during iteration. By investigating the simulation result, FDSA performs well in solving the 23 classic functions. FDSA can find the optimal global solution of nine functions.

Table 2. Comparison via existing

Authors and Year	Proposed	Advantages	Disadvantages
In 2019 S. M. Wasif,	Faster RCNN	It is the fastest among all the other algorithms	Need large amounts of annotated data to train and fine-tune, which can be costly, time-consuming
In 2023 J. He, and F. Zhu,	Single-Stage Heavy-Tailed Food Classification	5% improvements for top-1 accuracy.	Yet this method does not perform sequently
In 2022 T.B. Shahi,	Attention-convolution module based MobileNetV2 to classify the fruit images.	It requires a large number of trainable parameters although they claim that their models to be lightweight architectures.	Automatic fruit classification is an interesting problem
In 2022 H.S. Gill, and B.S. Khehra,	Proposed a scheme for classification of fruit images using deep learning applications.	Cross entropy is used to define the objective function of the problem	One of the major benefits to fusing deep learning model is that, they does not requires any hand crafted features.
In 2022 L. Jiang,	propose a three-step algorithm	proposed solution achieved comparable performance and has great potential to promote healthy dietary and feasible advice.	It is still time consuming to detect and classify the food in images.
In 2023 Y. Han,	ClusDiff	ClusDiff can help address the severe class imbalance issue in long -tailed food classification using the VFN-LT dataset.	However, such data dependency poses significant barriers to re al world applications, because acquiring a substantial, diverse, and balanced set of food images can be challenging.
In 2023 M. Mansouri,	MFOOD-32	The definition of benchmark dataset demands almost all the food types	Intra class variance problem of the food dataset

Meanwhile, FDSA is not so superior in solving fixed-dimension multimodal functions. By investigating the strategy dominance, implementing multiple directed searches improves performance significantly.

The main drawbacks of traditional methods are low accuracy, high variation in misclassification, and calorie content. To overcome this issue a novel DL-based food classification (SOOTYDEEPFIC) has been proposed.

3. Proposed methodology

In this section, a novel DL-based food items classification method (SOOTYDEEPFIC) was proposed to classify different foods from the dataset by caloric value. Fig. 1 illustrate the proposed methodology.

3.1 Data dataset

We utilized the dataset from [20] in this analysis. This dataset, which contains a total of 20 kinds and 20 types of fruits and vegetables, was utilized in this investigation. The data is separated into 16 distinct categories, including 8 for fruits and 8 for vegetables. Each class receives a distinct set of five veggies and fruits. There are, however, courses that only include four types of fruits and vegetables. Fruits and vegetables were photographed on various sized, shaped, and colored plates. The collection contains about 41,509 photos, with approximately 4,000 images each class.

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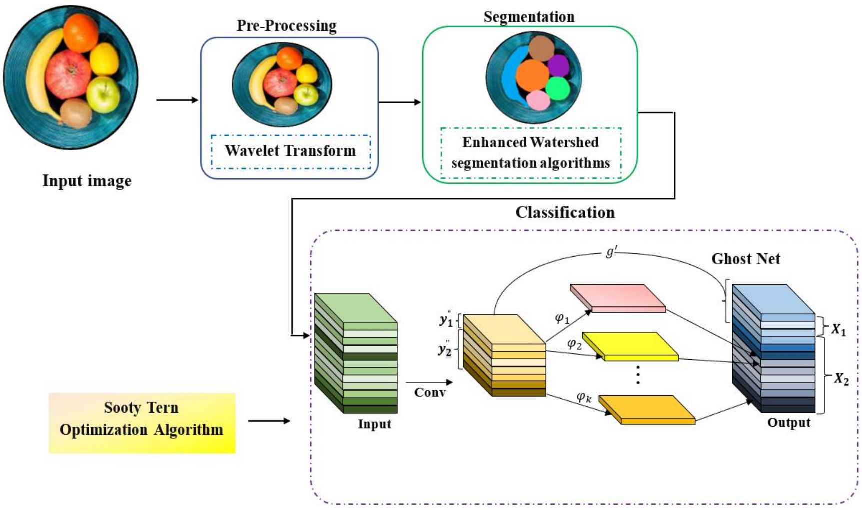

Figure. 1 Architecture of SOOTYDEEPFIC

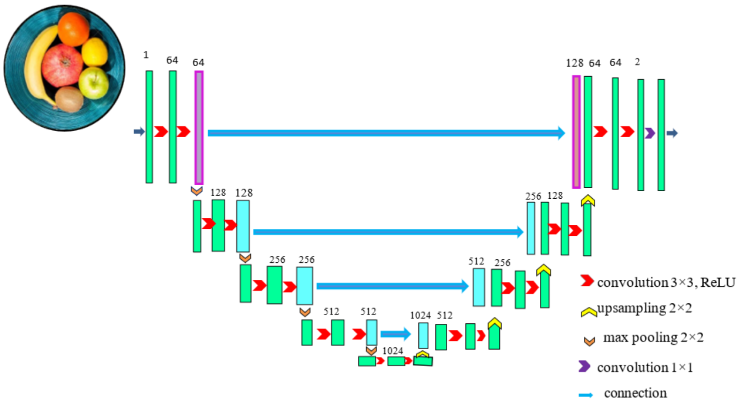

Figure. 2 Architecture of U-net

3.2 Pre-processing

Preprocessing images is a great way to enhance their quality and prepare them for analysis and further processing. Noise reduction, contrast improvement, picture scaling, color correction, segmentation, feature extraction, and other effective image preparation methods are available.

$$h(v,u) = \frac{1}{1+e^{(b\times(t-fs(v,u)))}} \quad (1)$$

The above equation (1) implies fs (v,u) - original image; h(v,u) - enhance pixel value; t - threshold value, b - contrast factor.

3.3 Segmentation

The pre-processed images are segmented using the U-NET ARCHITECTURE technique. The mathematical technique for morphological segmentation based on topology theory is called the U-NET ARCHITECTURE algorithm. The exact process of U-NET ARCHITECTURE algorithm is as follows. Architecture of U-net shown in Fig. 2.

The encoder (E) and decoder (D) network are joined to form a U network. Classical CNNs employed as encoders include more semantic data than spatial data. Segmentation, on the other hand, needs both semantic and geographical data. When instance normalization is applied, the modified linear unit (ReLU) is modified. There are 42 feature maps in the top layer's batch, and there are 3232 pixels in the patch. The entire slice will be effectively trained using four pooling procedures. Assume, the input is y_p in lth layer and (l, m) is the centre pixel of each patch on n-th feature.

$$q^{p}_{lmn}(t) = (w^{g}_{h})^{T} y^{g(l,m)}_{p}(t) + (w^{r}_{n})^{T}\, y^{r(l,m)}_{p}(t-1) + b_n \quad (2)$$

where the inputs of the convolutional layers are $y^{g(l,m)}_{p}$ and $y^{r(l,m)}_{p}(t-1)$. The weight of the

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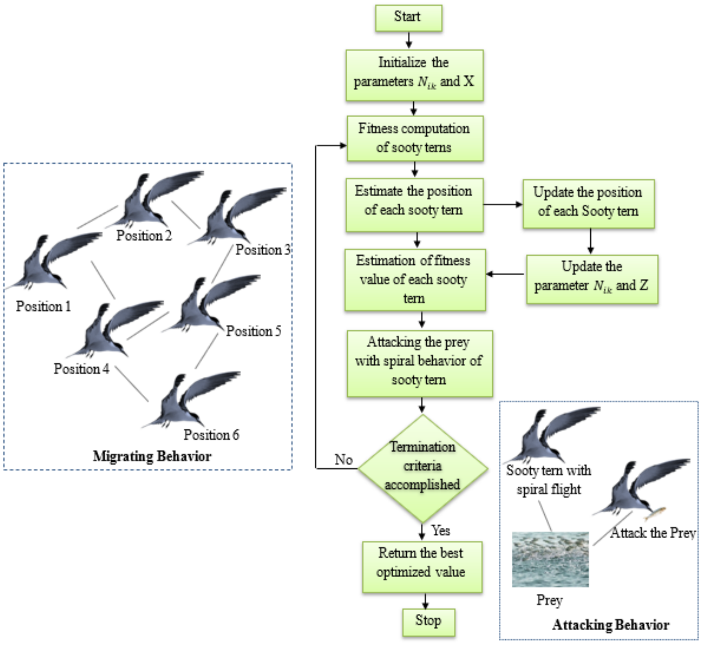

Figure. 3 Flowchart of STO algorithm

convolutional layers is $(w_h^g)^T$ and $(w_n^r)^T$. The bias is b_n.

$$g(y1k1) = g[q^p_{lmn}(t)] = \max[0, q^p_{lmn}(t)] \tag{3}$$

where y1k1 is the CNN unit's output. When encoding and decoding, this output is utilised to down- and up-sample.

3.4 Sooty tern

The STO method is based on the natural behavior and lives of seabirds and is used as a clustering technique to locate user groupings. The STO algorithm finds relevant communities based on the similarity metric. The transition operation and the attack operation are the two primary phases in the STO algorithm. Terns migrate in large groups. Scarlet terns choose separate starting locations to prevent clashes. Sooty terns can travel the same distance as humans despite their poor fitness levels.

3.5 Migrating behavior

In this phase, the obtained best solution from aquila optimization is further optimized using STO for creating the cluster. The sooty tern follows the three criteria to migrate successfully:

Collision avoidance:

The position of the search agent (SA) is computed to prevent conflict with nearby search agents (e.g., sooty terns).

$$a_{ij} = N_{ik} \times m_{ij}(p) \tag{4}$$

Converge in the direction of best neighbor: The search agents move in the direction of their closest neighbor to prevent collisions.

$$b_{ij} = X \times (Y_{best}(P) - m_{ij}(p)) \tag{5}$$

The greater exploration is represented by the random variable X. X is derived in Eq. (6):

$$X = 0.5 \times R_{and} \tag{6}$$

Where R_{and} is a random number that lies between the ranges from [0, 1].

Update corresponding to best search agent: The STO framework has been updated with new tactics based on quantum mechanics theories and trajectory analysis to improve performance. Flowchart of STO algorithm shown in Fig. 3.

It uses stochastic simulation to identify the elements that guarantee convergence. Updates are carried out using the following equations, by the quantum algorithm:

$$C_{ij}^{u+1} = S_{ij}^{u} \pm \alpha |Kbest_j^u - Z_{ij}^u| \ln \frac{1}{x} \tag{7}$$

$$c_{ij}^{u+1} = \begin{cases} S_{ij}^{u} \pm \alpha\left|Kbest_j^{u} - Z_{ij}^{u}\right| \ln\frac{1}{x}, & \text{if m and } (0,1) \geq 0.5 \\ S_{ij}^{u} \pm \alpha\left|Kbest_j^{u} - Z_{ij}^{u}\right| \ln\frac{1}{x}, & \text{otherwise} \end{cases} \quad (8)$$

$$c_{ij} = \rho c_{ij} + (1-\rho)c_{tj} \quad (9)$$

where C_{ij} denotes the gap between the search agent and the fittest search agent with maximum fitness value

3.6 Attacking behavior

In this phase, the selected best fitness users are clustered based on the similarity measure. During migration, these birds' wings assist them in reaching greater altitudes. The behavior is mathematically derived as,

$$l = S_{radius} \times \sin(i) \quad (10)$$

$$m = S_{radius} \times \cos(i) \quad (11)$$

$$n = S_{radius} \times j \quad (12)$$

$$D = a \times e^{kb} \quad (13)$$

where S_{radius} stands for the radius of each spiral round, i indicates that the variable within an interval of $\{0 \leq k \leq 2\pi\}$.

$$V_{ij}(p) = (C_{ij} \times (l + m + n)) \times Y_{best}(P) \quad (14)$$

where $V_{ij}(p)$ updates the positions of other SA and returns the best solution with clusters. The FC layer groups the pertinent user based on the output of the preceding layer using a few STO algorithmic clusters.

3.7 Ghost network

A deep learning-based ghost network is used for case classification. The discriminative capability of a lightweight convolutional neural network utilized for cervical cell categorization was increased by using a hybrid loss function with label smoothing. The most important thing is to split the first convolutional layer in half and use fewer filters to provide more unique feature mappings. The successful generation of ghost feature maps can thus be accomplished using a small number of accessible transformation techniques. Architecture of Ghost Network shown in Fig. 4.

Assume $y'' = y_1'' + y_2''(y_1'' < y_2''), y_1''$ are the basic feature info and y_2'' are redundant basic feature info, respectively. y_1'' utilized to create n intrinsic feature maps X_1. For each intrinsic feature map, linear operation ϕ_i is utilized to create k ghost feature maps. So, n intrinsic feature maps are generated $m = n * k$ ghost feature maps X_2. The n+m output convolution operation is displayed after the ghost convolution procedure, as follows:

$$X_1 = y_1'' \times g' \quad (15)$$

$$X_2 = y_{ij} = \varphi_i(x_i), \forall j = 1, \dots, n, i = 1, \dots, \quad (16)$$

$$X = X_1 \times X_2 \quad (17)$$

Where $g' \in T^{e*k*k*n}$ is the filter, $k \times k$ is the convolutional kernel size, n is the number of intrinsic feature maps $X_1 \in T^{h'*w'*m}$, w' and h' are the output feature maps breadth and height, and m is the number of ghost feature maps.

4. Result and discussion

The performance of the existing methods was compared with the performance of the proposed strategy to illustrate that it is more effective. In a comparative study, the SOOTY DEEPFIC is compared with three existing methods. SOOTY DEEPFIC model is compared to DL methods like. Performance evaluation was based on various metrics such accuracy of the DL technique.

4.1 Calorie estimation

The volume of the meal and an estimate of the caloric content are utilized to calculate the CV. CV are frequently utilized to quantify the entire amount of energy in each item, which includes the three major nutritional constituents, carbs, protein, and fat. Experimental results of the proposed SOOTYDEEPFIC shown in Fig. 5.

The table includes an example of a calorie Table. 3. Every day, a particular number of CV must be consumed. Obesity can result from eating too many calories each day.

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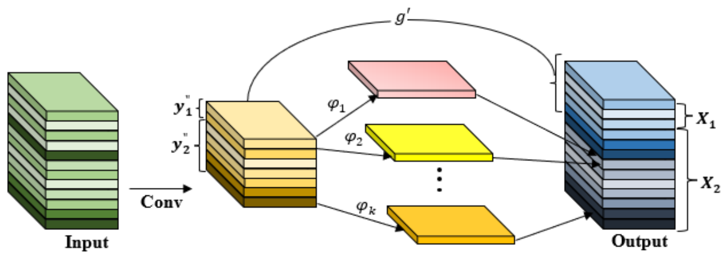

Figure. 4 Architecture of ghost network.

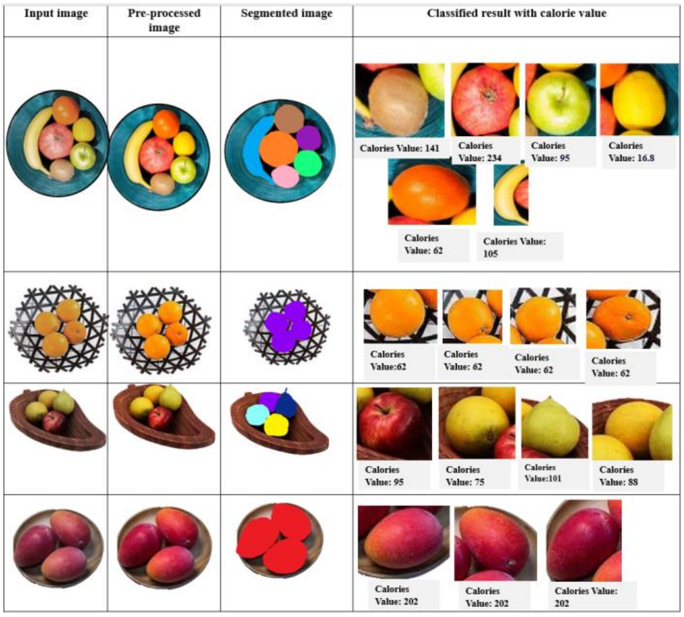

Figure. 5 Experimental results of the proposed SOOTYDEEPFIC

Algorithm: Sooty tern optimization

Input: population of users in social network
Output: Best cluster with best user Y_{best}
Procedure STO
Initialize the all the attributes
Calculate the fitness of each user using Eq. (4)
Update best user Optimal solutions can be achieved if they are better than the previous solution
Calculate the fitness of each cluster with the user
$Y_{best} \leftarrow$ the best cluster with user
For each cluster with a user do
Update the positions of the cluster with the user by using quantum theory Eq. 7, 8, 9
End for
Update the attributes SA and X
Calculate the fitness value of the cluster with the user
Update Y_{best} If there is a better solution than the previous optimal solution
return Y_{best}
end procedure

Table. 3 Common calories table

Food Name	**Measure**	**Weight (in grams)**	**Energy**
Banana	1	102	10
Orange	1	112	64
Mango	1	150	230
Apple	1	250	50
Chiku	1	170	166
Pomegranate	1	282	234
Pears	1	178	100

Fig. 6 illustrates the comparison of existing techniques, the ground truth contains 205 calories value for Mango fruits, proposed SootyDeepfic contains 202 calories value Existing ClusDiff contains 197 calories value, F-RCNN contains 192 calories value and DL applications used to classify fruit images contains 189 calories value for fruits.

In Fig. 7, the performance curve is illustrated by a vertical axis is illustrated as the accuracy range and a horizontal axis illustrates the number of epochs. As the number of epochs increases, the performance of the SOOTYDEEPFIC increases.

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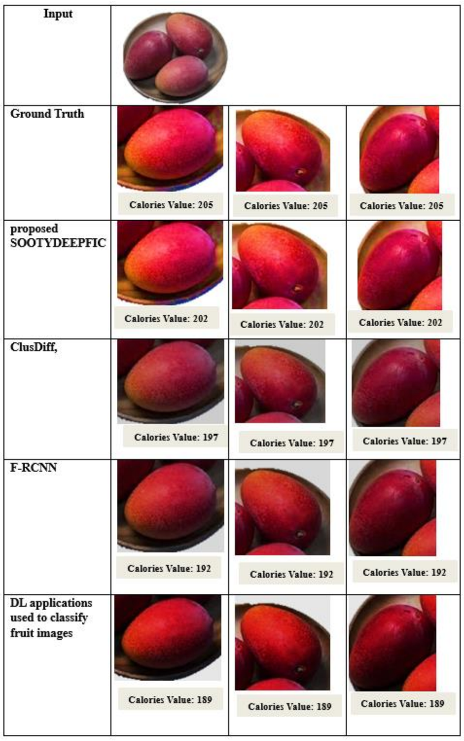

Figure. 6 Comparison of existing techniques

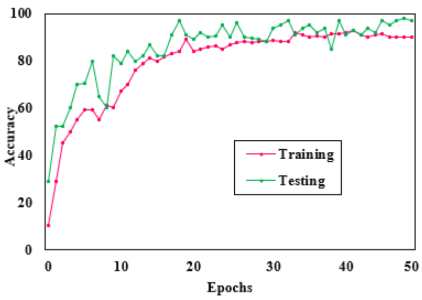

Figure. 7 Accuracy curve for the proposed model

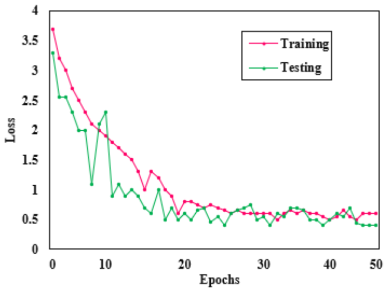

Figure. 8 Loss curve for the proposed model

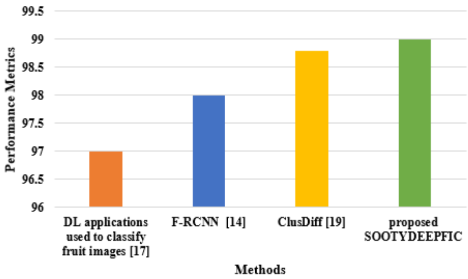

Figure. 9 Performance via accuracy

According to Fig. 8, the loss of the SOOTYDEEPFIC diminishes as the epochs are raised. The proposed SOOTYDEEPFIC obtains high accuracy for inpainting the video caption gaps using the dataset. This analysis defined the number of training epochs required to achieve a high level of testing accuracy.

Performance via accuracy shows in Fig. 9. The Proposed approach enhance the overall acc of the proposed SOOTYDEEPFIC, ClusDiff, F-RCNN and DL applications used to classify fruit images is 99%, 98.8%, 98% and 97 % individually.

5. Conclusion

In this research, a novel deep learning-based food classification algorithm (SOOTYDEEPFIC) was presented to identify different meals from datasets based on their CV. To begin, the image is stretched using the sigmoid technique to increase image quality and eliminate noise. As a consequence, the U-Net technique is used to segment the preprocessed picture. The sooty tern optimization algorithm (STOA) is used to normalize the retrieved characteristics. Ghostnet is used to categorize meals based on these key properties. The experimental result shows the proposed SOOTYDEEPFIC yields an overall accuracy is 99.89%. As compared to existing methods, the proposed SOOTYDEEPFIC shows better results in terms of Accuracy. The proposed approach enhances the overall accuracy of the suggested approach might overcome these difficulties in the future by utilizing hybrid DL techniques.

Conflicts of 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.

Author contributions

The authors confirm contribution to the paper as follows: Study conception and design: P. Josephin Shermila, V. Seethalakshmi; Data collection: P. Sujatha Therese; Analysis and interpretation of results: M. Devaki; Draft manuscript preparation: P. Josephin Shermila, V. Seethalakshmi. All authors reviewed the results and approved the final version of the manuscript.

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