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RESEARCH ARTICLE

Satin Bowerbird Optimization With Convolutional LSTM for Food Crop Classification on UAV Imagery

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ABSTRACT Food crop classification and identification are crucial aspects of modern agriculture. With progression of drones or unmanned aerial vehicles (UAVs), crop detection from RGB images goes through a paradigm shift from traditional image processing methods to deep learning (DL) methods due to effective breakthroughs in convolutional neural networks (CNN). Drone images are reliable for identifying different crops because of its higher spatial resolution. Food crop classification utilizing deep learning on drone images includes machine learning techniques for distinguishing and identifying different types of crops in images captured by UAVs. It is beneficial for various applications, like crop monitoring and precision agriculture. This paper presents a new Satin Bowerbird Optimization with deep learning for Food Crop Classification (SBODL-FCC) technique on UAV images. The presented SBODL-FCC technique exploits DL models with hyperparameter optimizers for food crop classification on UAV images. To accomplish this, the presented SBODL-FCC technique employs adaptive bilateral filtering technique for image preprocessing. Besides, the SBODL-FCC technique uses MobileNetv2 feature extractor with Bayesian optimization (BO) algorithm for parameter optimization. Moreover, the food crop classification process is performed through convolutional long short-term memory (ConvLSTM) model. Furthermore, the hyperparameter tuning of the ConvLSTM method is accomplished through SBO algorithm. The experimental validation of the SBODL-FCC technique is validated on UAV image database and the results are inspected under different aspects. The simulation outcomes inferred that the SBODL-FCC technique reaches better performance over other models in terms of several performance measures.

INDEX TERMS Unmanned aerial vehicles, food crop, image classification, deep learning, agriculture, metaheuristics.

I. INTRODUCTION

Achieving food security for an increasing population worldwide would need considerable progress in market building, local capacity, and technology. A key element of enlightening food security in the near terminology is more detailed data on seasonal crop productivity, made available as quickly as possible during growing season and upgraded as conditions change [1]. Remote sensing (RS) from unmanned aerial vehicles (UAVs) and satellites can enrich the accuracy and timeliness of agricultural data and augment ground surveys. Timely and accurate information about the crop state is a key component to increasing agricultural crops that could be done by means of effective RS technology [2]. Furthermore, a robust algorithm is crucial to efficiently exploit RS information.

Crop classification is the important key in advanced agriculture that attempts to classify plant and crop types into various classes while determining the spatial distribution [3]. It helps farmers and government authorities to have effective data regarding the crops that are used to enhance the capabilities of making decisions. A great number of studies have

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been conducted on precise crop classification from satellite-based RS images with the use of machine learning (ML) and deep learning (DL) techniques accomplishing impressive performance [4]. On the other hand, they have numerous obstacles like different weather conditions that have made data collection extremely challenging, and low spatial or temporal resolutions that must have adverse effects on data quality. Such constraints may decline the performance of the algorithm resulting in incorrect crop classification [5]. Furthermore, conventional techniques to categorize different types of plants or crops from aerial imagery have depended on traditional ML, together with Random Forest (RF) and Support Vector Machine (SVM) techniques [6].

Amongst several crop classification techniques, DL algorithm is becoming more and more frequent in the field of crop detection and is considered a breakthrough technology [7]. DL network has a more complex and deeper structure that could learn the feature automatically inside the network layer, to accomplish improved crop detection. During crop classification and recognition, few crops are hard to determine because of low resolution of crop mapping, similar spectral features, and salt and pepper noise that have a serious effect on the performance of crop recognition and classification [8]. With the ongoing progress of RS technologies, it can able to perform a large number of crop classification studies by using RS images [9]. With traditional classification methods to extract RS information is generally challenging to apply the high dimensional feature covered by an image, and the classification effects are poor. Deep learning (DL) technique could learn deep feature of images, extracts them efficiently, and make decision based on the target requirement [10]. Recently, the application scope of DL has been further extended that bring a new technique to attain best classification performance of UAV RS images.

This paper presents a new Satin Bowerbird Optimization with deep learning for Food Crop Classification (SBODL-FCC) technique on UAV images. The presented SBODL-FCC technique employs adaptive bilateral filtering (ABF) technique for image preprocessing. Besides, the SBODL-FCC technique uses MobileNetv2 feature extractor with Bayesian optimization (BO) algorithm for parameter optimization. Moreover, the food crop classification process is performed through convolutional long short-term memory (ConvLSTM) model. Furthermore, the hyperparameter tuning of the ConvLSTM model is accomplished by the use of SBO technique. The experimental validation of the SBODL-FCC technique is validated on UAV image database and the outcomes are inspected under different aspects.

II. RELATED WORKS

In [11], the authors make use of RGB images gathered from drones flown in Rwanda for developing a DL technique to detect crop types, particularly legumes, bananas, and maize, which were main strategic food crops in Rwandan agriculture. The method uses advancements in deep CNNs and TL, using the VGG16 structure and openly available ImageNet dataset for pre-training. Reedha et al. [12] intend to show that the attention-related deep network was an auspicious method for addressing the abovementioned issues, with regard to context of crops and weed recognition with drone mechanism.

Razfar et al. [13] presented a vision-based weed detection mechanism utilizing DL approaches that successfully identify weeds within a soybean plantation. Five DL techniques were utilized, which include three custom CNN techniques, MobileNetV2, and ResNet50. Tetila et al. [14] modelled the outcomes of the assessment of 5 DL architectures for classifying soybean pest imageries. The performance of VGG-19, Inception-v3, Resnet-50, Xception and VGG-16, has been assessed for distinct fine-tuning and TL approaches over a dataset of 5,000 imageries captured in real time conditions. In [15], the aim was to find maize leaves that were infected by fall armyworms (faw) by utilizing automatic recognition methods depends on the CNN namely, InceptionV3, VGG16, MobileNetV2 and VGG19. Such techniques are utilized for investigating the infected maize leaves that have been taken through an UAV-RS technologies.

Pan et al. [16] modelled a DL-related technique to find wheat yellow rust from drone images. The technique depends on the pyramid scene parsing network (PSPNet) semantic segmenting method for categorizing bare soil in small-scale drone images, healthy wheat, and yellow rust wheat. Moreover, it has been modelled to use the high-accuracy classifier outcomes of conventional techniques as weak samples for wheat yellow rust detection. In [17], the UAV image has been captured on 4 distinct dates than 2 distinct rice domains D and Object-based image analysis (OBIA) and techniques are applied to the weed mapping task of the UAV image. For the OBIA techniques, the multiresolution segmentation and method were implemented for segmenting the image various distinct objects; the texture and colour were concatenated and extracted into a feature vector; random forest (RF) BP-SVM and neural network are utilized for classification.

In [18], an enhanced NMS-based max intersection over portion (MIoP-NMS) technique was presented for addressing this problem and execution in the YOLOv4 network structure to single-stage target recognition. Pandey and Jain [19] examines a novel conjugated dense CNN (CD-CNN) structure with a novel activation function termed as SL-ReLU for intelligent classification of several crops in RGB images taken by UAV. CD-CNN combines data fusion and mapping feature extraction from conjunction with classifier procedure.

Chaudhari et al. [20] focuses in the development of Bayesian optimization with DL driven crop type classification (BODLD-CTC) approach. For attaining this, the projected BODLD-CTC algorithm executes Xception method as extraction feature. For classification methods, the LSTM technique was utilized. Juyal and Sharma [21] examines a technique to apply field surveillance by utilizing UAV for assigning a grade to all the fields that can be connected to crop growth. On a banana planting, this technology is

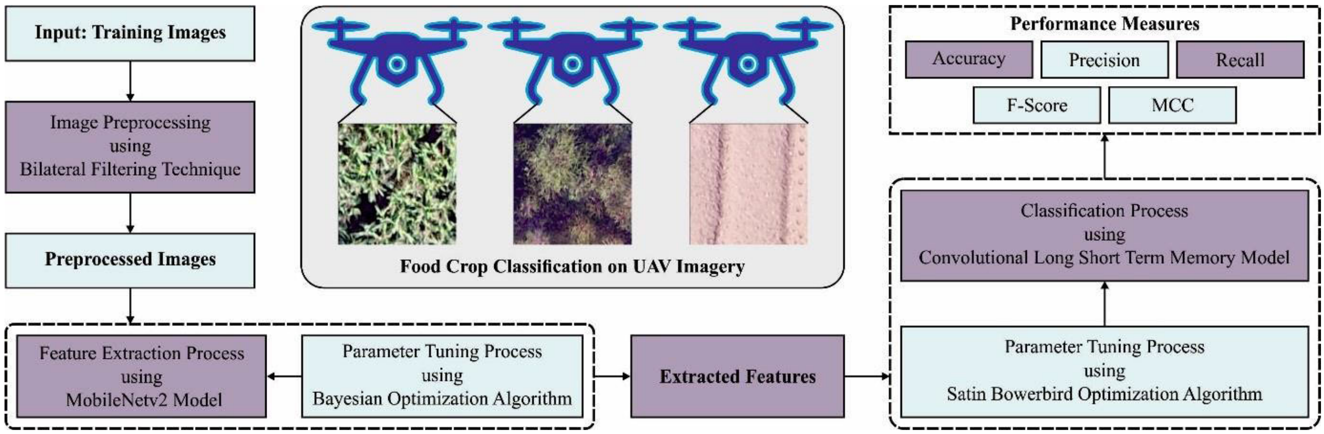

FIGURE 1. **Overall flow of SBODL-FCC system.**

demonstrated among them made it modular that utilized without need to huge effort to various crops.

Several models are existed in the literature to perform classification process. Though several ML and DL models for crop classification are available in the literature, it is still needed to enhance the classification performance. Owing to continual deepening of the model, the number of parameters of DL models also increases quickly which results in model overfitting. At the same time, different hyperparameters have a significant impact on the efficiency of the CNN model. Particularly, the hyperparameters such as epoch count, batch size, and learning rate selection are essential to attain effectual outcome. Since the trial and error method for hyperparameter tuning is a tedious and erroneous process, metaheuristic algorithms can be applied. Therefore, in this work, we employ SBO algorithm for the parameter selection of the ConvLSTM model.

III. THE PROPOSED MODEL

In this article, we have developed a new SBODL-FCC method for automated food crop classification process on the UAV images. The presented SBODL-FCC technique employed the concepts of DL and hyperparmaeter tuning for food crop identification process. It comprises a series of processes such as ABF based noise removal, MobileNetv2 feature extractor, BO based parameter tuning, ConvLSTM based classification, and SBO based hyperparameter optimization. Fig. 1 demonstrates the overall flow of SBODL-FCC approach.

A. IMAGE PREPROCESSING

Primarily, the presented SBODL-FCC technique employed ABF technique for image preprocessing. ABF can be refereed as variant of bilateral filter where the weights were determined adaptively on the basis of the local image content [22]. This can further enrich the performance of the filter by considering the particular features of the image, like the presence of large intensity variations or strong edges. ABF was a type of image processing method that can be utilized to smooth images while protecting edges and other significant details. It functions by implementing a weighted average to pixels in an image, with weights being determined by both the intensity difference between them and spatial distance among pixels.

B. FEATURE EXTRACTION USING OPTIMAL MOBILENET MODEL

In this work, the SBODL-FCC technique uses MobileNetv2 feature extractor. It is chosen due to the following merits: high performance, low computation cost, lightweight, fast inference, and compatible with limited memory. MobileNet is a framework that is designed to be worked on embedded devices or systems and mobiles, which lack computation power [23]. This framework was introduced by Google. Depthwise convolution was exploited in MobileNet framework for dramatically decreasing the number of trained parameters than typical CNN which have comparable depth. The depthwise convolutional layer handles the spatial dimension together with depth dimension (number of channels). Depthwise convolutional layer splitting the kernels into 2 smaller kernels, one for depthwise convolution and other for pointwise convolutional layer. This splitting of kernel decreases computation costs significantly. MobileNet provides the outcome that is similar to AlexNet while considerably decreasing the trained parameters. In this work, a pretrained MobileNet architecture (trained on ImageNet data) is introduced. The Pretrained model is exploited due to the lack of largescale dataset for the detection. Dense layer of 128×1 replaces the classification models that are head of the model, 3×1 and 128×1, 2×1 for binary and ternary classification, respectively. Then, the method is finetuned on input image for effective performance. During finetuning, MobileNetV2 provides input image of $224 \times 224 \times 3$ dimensions. Then, the input undergoes depthwise and pointwise convolutional layers at different times. Finally, the feature attained from the abovementioned processes are given into two dense layers of 128 × 1 and 3 × 1 or 2 × 1 dimensions for classification.

For the enhancement of the performance of the MobileNetv2 method, the BO algorithm is applied. BO functions by building a posterior distribution of functions that can be gaussian process that better defines the function to optimize [24]. The posterior distribution enhances, once the number of comments increases, and the algorithm is certain of which areas in parameter space were computing and worth exploring. BO technique contains 2 main elements: one is acquisition function to determine where sampling next one and another one is Bayesian statistical model for modelling the main function. The function will trade off exploration and exploitation. Exploitation can be referred as sample in which the Bayesian statistical method estimated maximum objective scores.

Return a solution: either the point assessed with largest (x), or the point with largest posterior mean. Sampling at locations in which the estimation uncertainty was maximum. Both contributed to higher acquisition function value and the objective was to maximize the acquisition function for determining next sample points. After assessing the goal related to an opening space-filling experimental model, often consisting points selected regularly at random, it is utilized iteratively for allocating a budget remainder of N function assessments. The time complexities for DL are $(w \cdot m \cdot e)$, where w signifies, m denotes the count of learning samples, and e indicated the running epochs. For BO, the time complexity is (n^3), where n is observations. In this study, the number of filters that are used in all attention layers is maximized. For hyper parameter tuning with BO, the author constructed a main function which have taken the filters in all attention layers as input and returns test accuracy score.

C. FOOD CROP CLASSIFICATION USING CONVLSTM

Here, the food crop classification process is performed through the ConvLSTM model. LSTM-DNN model is a kind of Recurrent Neural Network (RNN) that excels in modelling temporal behaviors like | text, language, audio and time series, owing to the additional parameter metric available for the connection among time steps along with the feedback loop used for learning [25]. The main component of LSTM is forget gate, input gate, output gate and memory cells. They allow the LSTM model to have connection from time layers and prior steps, whereby all the outputs are based on the input and the previous inputs. Typically, there are more than one LSTM layers, whereby all the layers consist of multiple LSTM units, and all the units comprise input, output, and forget gates. The equation for input, output, and forget gates, along with the cell state, the LSTM cell output, and the candidate cell state, were correspondingly defined as follows:

$$i_t = \sigma\left(W_{hi} h_{t-1} + W_{xi} x_t + b_i\right) \tag{1}$$
$$f_t = \sigma\left(W_h f h_{t-1} + W_x f x_t + bf\right) \tag{2}$$
$$0_t = \sigma\left(W_{ho} h_{t-1} + W_{xo} x_t + b_0\right) \tag{3}$$
$$C_t = tanh\left(W_{hC} h_{t-1} + W_{xC} x_t + b_C\right) \tag{4}$$
$$C_t = f_t C_{t-1} + (1 - f_t)\tilde{C}_t \tag{5}$$
$$h_t = 0_t tanh\left(C_t\right) \tag{6}$$

Now i denotes the input gate, f refers to the forget gate, 0 indicates the output gate, C_t shows candidate cell state, C represents cell state, h denotes the hidden state and cell output, σ signifies a logistic sigmoid function, W shows the weight matrix, and b denotes the bias vector. Fig. 2 represents the framework of ConvLSTM.

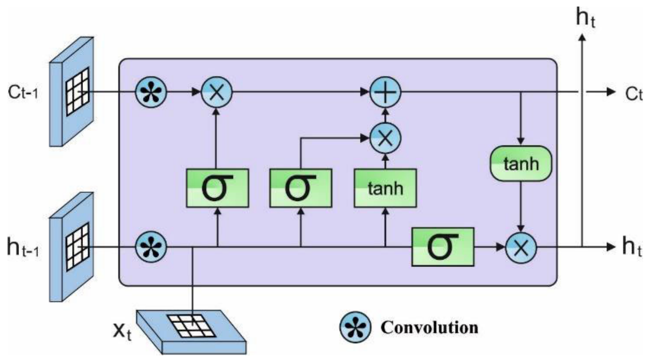

FIGURE 2. Structure of ConvLSTM.

ConvLSTM is a kind of LSTM that developed to precisely model the spatiotemporal data, by leveraging the strength of LSTM and CNN. Like LSTM, the ConvLSTM is capable of deciding what data to be discarded or retained from the earlier cell state in its existing cell state. On the other hand, convolutional structure is applied on both state-to-state and input-to-state transitions that usually exchange internal matrix multiplication with convolutional operation. The input vector to the ConvLSTM can be given fed as a sequence of $2D$ or $3D$ imageries since the convolutional operation enables the information that passed over ConvLSTM cell to keep the inputted dimension rather than being a 1D vector with feature. To define the ConvLSTM operation, Eqs (1) and (6) are formulated by:

$$i_t = \sigma\left(W_{Ci} \circ C_{t-1} + W_{hi} * h_{t-1} + W_{xi} * x_t + b_i\right) \tag{7}$$
$$f_t = \sigma\left(W_{C} f \circ C_{t-1} + W_{hf} * h_{t-1} + W_{xf} * x_t + b_f\right) \tag{8}$$
$$0_t = \sigma\left(W_{Co} \circ C_t + W_{ho} * h_{t-1} + W_{xo} * x_t + b_0\right) \tag{9}$$
$$\mathrm{C}_t = tanh\left(W_{hC} * h_{t-1} + W_{xC} * x_t + b_C\right) \tag{10}$$
$$C_t = f_t \circ C_{t-1} + (1 - f_t) \circ \tilde{C}_t \tag{11}$$
$$h_t = 0_t \circ tanh\left(C_t\right) \tag{12}$$

From the above equations, $\circ$ signifies the Hadamard product, $*$ shows the convolution operators, W_{Ci}, W_{hi}, W_{xi}, W_C, W_h, W_x, W_{Co}, W_{ho}, W_{xo}, W_{hC}, W_{xC} $\in \mathbb{R}^{n \times T}$ represents the convolution kernel within the model, and b_i, b_f, b_0, b_C shows the bias parameter. The architecture of ConvLSTM, where the red line indicates the additional connection was found in ConvLSTM cell over LSTM cell that comes from present and prior cell states.

D. HYPERPARMETER TUNING USING SBO ALGORITHM

Lastly, the hyperparameter tuning of the ConvLSTM method is accomplished by the use of SBO algorithm. SBO technique starts producing a uniform arbitrary population which comprises a group of places to bower [26]. SBO algorithm has the following characteristics: global optimization, easy to implement, less number of parameters, robust, and highly efficient. Each position (pop(i).Pos) can be defined to the variable that is assumed that enhance as given in Eq. (14). It is noted that the value of initial population lies amongst the present minimal and maximal limit of enhancing parameter.

$$pop(i).Pos = rand(1,n_{var}) \cdot (Var_{\mathrm{Max}} - Var_{\mathrm{Min}}) + Var_{\mathrm{Min}}, \forall i \in n_{Pop} \tag{13}$$

Relatively, similar to ABC, the probability of fascinating of male/female ($Prob_i$) to bower was evaluated by:

$$Prob_i = \frac{cost_i}{\sum_{k=1}^{n_{Pop}} cost_i}, \forall i \in n_{Pop} \tag{14}$$

$$\mathrm{cost}_i = \begin{cases} \frac{1}{1+f(x_i)}, & f(x_i) \geq 0 \\ 1 + |f(x_i)|, & f(x_i) < 0 \end{cases} \tag{15}$$

Like other evolutionary based on optimizer, elitism was exploited to store an optimal solution at every iteration. During mating, males like every bird utilizes its drives for decorating and building the bower. Remarkably, experienced and older males are attracted more consideration of others to the bower. On the other hand, these bowers have additional fitness than the other bower. In the SBO process, the location of optimal bower generated by bird was assessed as elite of k^{th} iteration ($x_{elite,k}$) viz., highest fitness and able to affect the other locations. In each iteration, a novel modification at certain bower was calculated based on the following expression:

$$\chi_{ik}^{new} = \chi_{i,k}^{old} + \beta_k \left[\left(\frac{x_{jk} + x_{elite,k}}{2} \right) - \chi_{i,k}^{old} \right] \tag{16}$$

Note that roulette wheel selective technique was exploited for selecting bower with better probability (x_{jk}). In SBO, variable β_k determines the step count select target bower that is evaluated to each variable as:

$$\beta_k = \frac{\alpha}{1 + Prop_i} \tag{17}$$

Arbitrary modification was implemented to x_{ik} with certain probability, where normal distribution (N) was exploited by the variance of σ and average of $x_{i,k}^{old}$ as follows:

$$X_{ik}^{ne\omega} \sim X_{ik}^{old} + \sigma \cdot N(0, 1)$$
$$\sigma = Z \cdot (Var_{\mathrm{Max}} - Var_{\mathrm{Min}}) \tag{18}$$

Lastly, each cycle is an older population and population obtained as abovementioned were sorted, integrated, assessed and novel population was generated.

The SBO method derived a fitness function (FF) to have enhanced classifier outcome. It determined positive values for signifying the superior performance of the candidate solutions. In this article, the reduced classifier error rate is the FF, as given in Eq. (19).

Algorithm 1 Pseudocode of SBO Algorithm

Input: Population $\vec{P_{sp}}$
Output: Optimum search agent, $\vec{P_{bst}}$
Procedure SOA
    Parameter Initialization: C_A and C_B
    Define the fitness of each searching agent
    $\vec{P_{bst}} \leftarrow$ optimum search agent
    While ($z < Max_{iterations}$) *do*
        for all the searching agents do
            Upgrade the position of search agent
        end for
        Upgrade parameters C_A and C_B
        Define fitness value of each search agent
        Upgrade $\vec{P_{bst}}$ if best solution exists over earlier optimal solution
        $z \leftarrow z + 1$
    End while
    Return $\vec{P_{bst}}$
End process

$$\begin{aligned} fitness(x_i) &= ClassifierErrorRate(x_i) \\ &= \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \end{aligned} \tag{19}$$

IV. RESULTS AND DISCUSSION

The proposed model is simulated using Python tool. The proposed SBODL-FCC technique is validated using the UAV food crop dataset [27], comprising 6450 samples as represented in Table 1. The dataset holds samples with six class labels.

TABLE 1. Details of dataset.

Class	No. of Images
Maize	2075
Banana	1661
Forest	1270
Other	750
Legume	363
Structure	331
Total Number of images	6450

The confusion matrix of the SBODL-FCC technique on food crop classification outcomes is demonstrated in Fig. 3. The figure shows that the SBODL-FCC approach proficiently recognizes different types of food crops.

In Table 2 and Fig. 4, the food crop classification results of the SBODL-FCC method with 80:20 of TRS/TSS are given. The results implied that the SBODL-FCC technique obtains enhanced performance with the classification of six different classes. For instance, with 80% of TRS, the SBODL-FCC technique accomplishes average $accu_y$ of 96.49%, $prec_n$ of 88.88%, $reca_l$ of 85.22%, F_{score} of 86.87%, and MCC of

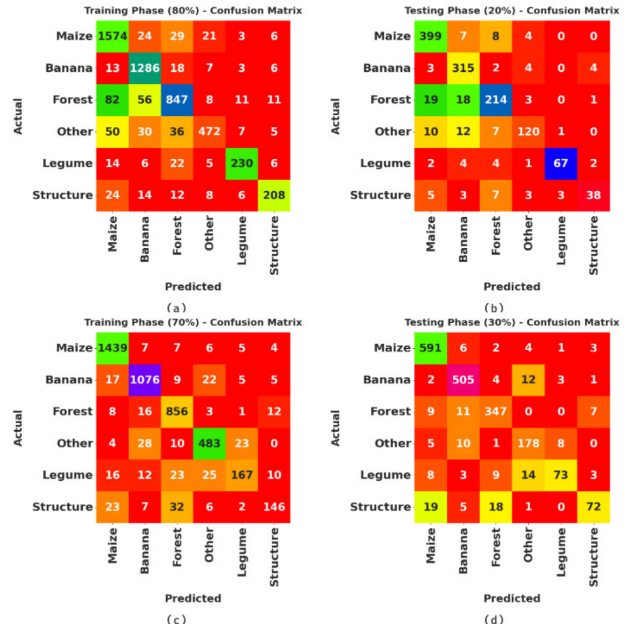

FIGURE 3. Confusion matrices of SBODL-FCC system (a-b) TRS/TSS of 80:20 and (c-d) TRS/TSS of 70:30.

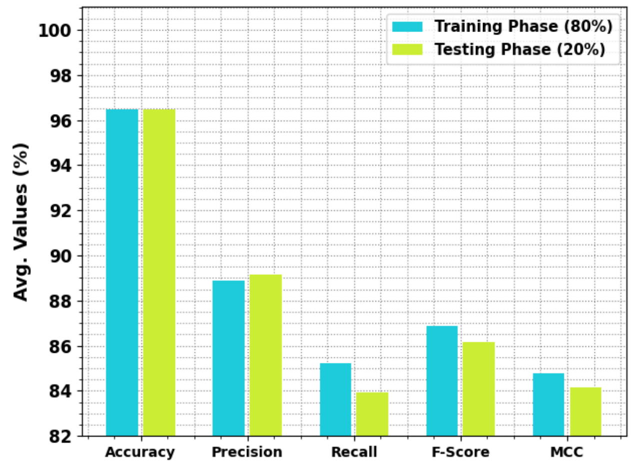

FIGURE 4. Average outcome of SBODL-FCC system on 80:20 of TRS/TSS.

TABLE 2. Food crop classifier outcome of SBODL-FCC system on 80:20 of TRS/TSS.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	MCC
Training Phase (80%)					
Maize	94.84	89.58	94.99	92.21	88.45
Banana	96.57	90.82	96.47	93.56	91.30
Forest	94.48	87.86	83.45	85.60	82.23
Other	96.57	90.60	78.67	84.21	82.56
Legume	98.39	88.46	81.27	84.71	83.95
Structure	98.10	85.95	76.47	80.93	80.09
Average	96.49	88.88	85.22	86.87	84.76
Testing Phase (20%)					
Maize	95.50	91.10	95.45	93.22	89.92
Banana	95.58	87.74	96.04	91.70	88.87
Forest	94.65	88.43	83.92	86.12	82.85
Other	96.51	88.89	80.00	84.21	82.40
Legume	98.68	94.37	83.75	88.74	88.22
Structure	97.83	84.44	64.41	73.08	72.68
Average	96.46	89.16	83.93	86.18	84.16

TABLE 3. Food crop classifier outcome of SBODL-FCC system on 70:30 of TRS/TSS.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	MCC
Training Phase (70%)					
Maize	97.85	95.49	98.02	96.74	95.16
Banana	97.17	93.89	94.89	94.39	92.49
Forest	97.32	91.36	95.54	93.40	91.75
Other	97.19	88.62	88.14	88.38	86.78
Legume	97.30	82.27	66.01	73.25	72.32
Structure	97.76	82.49	67.59	74.30	73.54
Average	97.43	89.02	85.03	86.74	85.34
Testing Phase (30%)					
Maize	96.95	93.22	97.36	95.25	93.05
Banana	97.05	93.52	95.83	94.66	92.64
Forest	96.85	91.08	92.78	91.92	89.97
Other	97.16	85.17	88.12	86.62	85.04
Legume	97.47	85.88	66.36	74.87	74.24
Structure	97.05	83.72	62.61	71.64	70.95
Average	97.09	88.76	83.84	85.83	84.31

84.76%. Afterwards, with 20% of TSS, the SBODL-FCC method accomplishes average $accu_y$ of 96.46%, $prec_n$ of 89.16%, $recal_l$ of 83.93%, F_{score} of 86.18%, and MCC of 84.16%.

In Table 3 and Fig. 5, the food crop classification results of the SBODL-FCC method with 70:30 of TRS/TSS are given. The results implied that the SBODL-FCC approach obtains enhanced performance with the classification of six different classes. For example, with 70% of TRS, the SBODL-FCC method accomplishes average $accu_y$ of 97.43%, $prec_n$ of 89.02%, $reca_l$ of 85.03%, F_{score} of 86.74%, and MCC of 85.34%. Then, with 30% of TSS, the SBODL-FCC method accomplishes average $accu_y$ of 97.09%, $prec_n$ of 88.76%, $reca_l$ of 83.84%, F_{score} of 85.83%, and MCC of 84.31%.

The TACY and VACY of the SBODL-FCC technique are investigated on food crop classifier performance in Fig. 6. The figure shows that the SBODL-FCC approach has shown improved performance with increased values of TACY and VACY. Notably, the SBODL-FCC technique has reached higher TACY outcomes.

The TLOS and VLOS of the SBODL-FCC approach are tested on food crop classifier performance in Fig. 7. The figure inferred that the SBODL-FCC method has revealed better performance with least values of TLOS and VLOS.

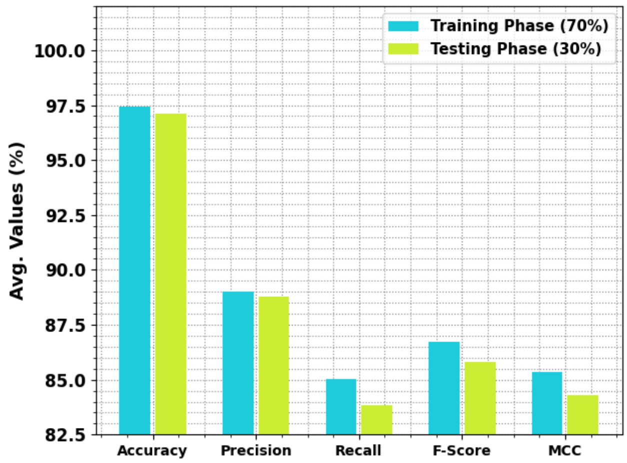

FIGURE 5. Average outcome of SBODL-FCC system on 70:30 of TRS/TSS.

FIGURE 6. TACY and VACY outcome of SBODL-FCC system.

FIGURE 7. TLOS and VLOS outcome of SBODL-FCC system.

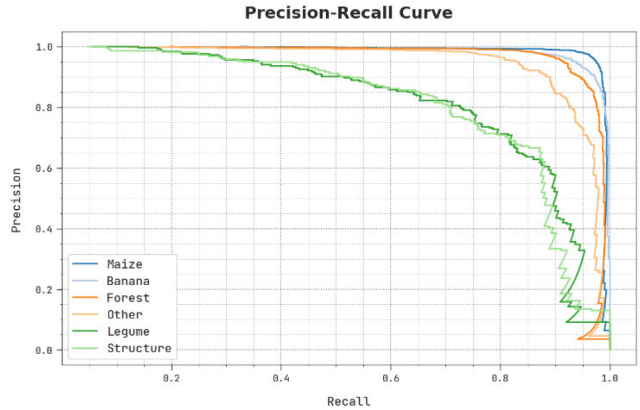

FIGURE 8. Precision-recall outcome of SBODL-FCC system.

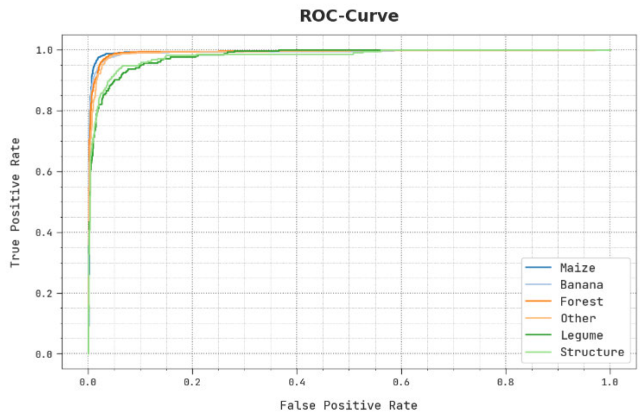

FIGURE 9. ROC outcome of SBODL-FCC system.

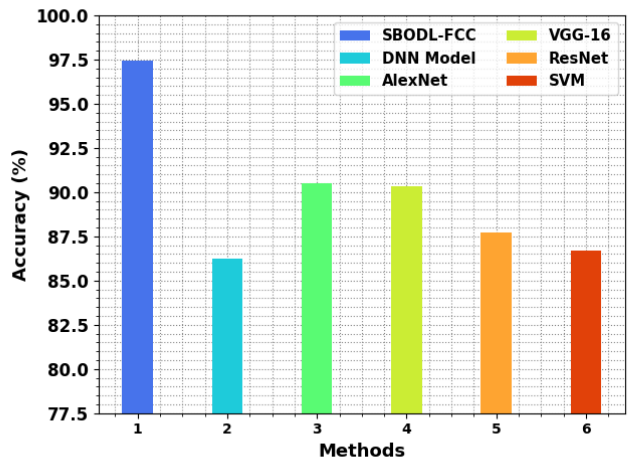

FIGURE 10. $Accu_y$ outcome of SBODL-FCC approach with other existing systems.

Seemingly the SBODL-FCC method has reduced VLOS outcomes.

A clear precision-recall analysis of the SBODL-FCC technique under test database is given in Fig. 8. The figure specified that SBODL-FCC algorithm has enhanced values of precision-recall values under all classes.

The detailed ROC study of the SBODL-FCC approach under test database is shown in Fig. 9. The outcomes designated the SBODL-FCC method have revealed its ability in categorizing distinct classes.

In Table 4 and Fig. 10, a brief comparative study of the SBODL-FCC technique with existing models is made [11].

TABLE 4. Comparative outcome of SBODL-FCC approach with other existing systems [11].

Methods	Accuracy	Precision	Recall	F-Score
SBODL-FCC	97.43	89.02	85.03	86.74
DNN Model	86.23	86.11	84.39	86.29
AlexNet	90.49	87.68	81.70	83.36
VGG-16	90.35	85.28	81.35	85.70
ResNet	87.70	86.42	81.18	83.02
SVM	86.69	87.99	83.61	84.21

The experimental values represented that the DNN, ResNet, and SVM models obtain poor performance with least classification $accu_y$ values of 86.23%, 87.70%, and 86.69% respectively.

Moreover, the VGG-16 and AlexNet models accomplish moderately closer $accu_y$ of 90.35% and 90.49% respectively. However, the SBODL-FCC technique results in maximum $accu_y$ of 97.43%, $prec_n$ of 89.02%, $reca_l$ of 85.03%, and F_{score} of 86.74%. These results reassured the better performance of the SBODL-FCC technique over other models.

V. CONCLUSION

In this article, we have developed a new SBODL-FCC technique for automated food crop classification process on UAV images. The presented SBODL-FCC technique employed ABF technique for image preprocessing. Followed by, the SBODL-FCC technique uses MobileNetv2 feature extractor with the BO algorithm for parameter optimization. Moreover, the food crop classification process is performed through the ConvLSTM model. Furthermore, the hyperparameter tuning of the ConvLSTM method is accomplished through SBO method. The experimental validation of the SBODL-FCC technique is validated on UAV image database and the results are inspected under different aspects. The simulation values inferred that the SBODL-FCC technique reaches better performance over other models in terms of several performance measures. In future, the performance of SBODL-FCC method will be boosted by hybrid DL classification model. Besides, the proposed model can be tested on large scale real time dataset.

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