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Optimal Deep Learning Driven Smart Sugarcane Crop Monitoring on Remote Sensing Images

Ahmed Kareem Shakir¹¹ information technology Department, college of engineering, university of Qom, Tehran, Iran

*Corresponding author: Ahmed Kareem Shakir (email: ahmedalkhayyat85@iunajaf.edu.iq)

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Abstract: Crop monitoring is a process that involves regular field visits that seem to be difficult since it needs a huge amount of time and manpower. Thus, in modern agriculture, with an extensive range of satellite data such as Landsat, Sentinel-2, Modis, and Palsar, data are readily available. Sugarcane is a tall perennial grass belonging to the genus *Saccharum*, utilized for producing sugar. These plants were generally 2–6 m tall with fibrous, stout, jointed stalks, rich in sucrose, that will be accumulated in the stalk internodes. Sugarcane has a different growth pattern and phenology than many other crops; thus, the spectral and temporal features of satellite data are examined by utilizing statistical and machine learning (ML) techniques for optimal discrimination of sugarcane fields with other crops. In this study, we propose an Optimal Deep Learning Driven Smart Sugarcane Crop Monitoring (ODLD-SSCM) model on Remote Sensing Images. The presented ODLD-SSCM model mainly intends to estimate the crop yield of sugarcane using RSIs. In the presented ODLD-SSCM technique, the sugarcane yield mapping can be derived by the use of the self-attentive deep learning (SADL) model. Besides, an oppositional spider colony optimization (OSCO) algorithm is used for the hyperparameter tuning of the ODLD-SSCM model. A detailed set of experimentations were performed to demonstrate the enhanced outcomes of the ODLD-SSCM model. A comprehensive comparison study pointed out the enhancements of the ODLD-SSCM model over other recent approaches.

Keywords: Crop monitoring; remote sensing images; yield mapping; sugarcane; deep learning.

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1. Introduction

Remote sensing (RS) refers to an effective source of data for site-specific crop monitoring, offering spatial and temporal data [1]. Orbital imageries were typically utilized in the agricultural sector for finding spectral differences resultant from crop and soil features at a large-scale, supportive diagnostics for agronomical crop variables, and help the agriculturalists in making superior management decisions [2]. For example, over the years, orbital images are employed to demarcate management areas for annual crops, observe in-field yield variability for several crops like cotton and corn, develop crop growth

models, map vineyard variability, map grasslands biomass, and plan the wheat harvest among others [3]. Certain main limits based on orbital images were lacking the measurement accuracy and ground truth data of the agronomical variables. Additionally, the empirical methods for predicting agronomical variables related to spectral data might have spatial and temporal limitations for implementation over various seasons and fields [4]. For the sugarcane, the valuation of the spatial changeability becomes difficult because of the restricted adapted solutions majorly for yield mapping.

Owing to its exclusive phenological stages, sugarcane is one distinct growing paradigm as articulated in the time sequence of data, typically spanning all over the year [5]. In the Germination stage, the tiny sprouts appear whereas, in the Tillering stage, the plants advance quickly deprived of elongation. In the third stage, named the grand growth stage, there will be a stem extension trailed by the significant leaf extension [6]. The last stage is the maturity stage in which the crop will lose its chlorophyll content and vigour, not appropriate for harvest. Sugarcane is a commercial crop that can be harvested related to the capability of market demands and sugar mills [7]. This lively nature of the harvesting period imposes difficulty on sugarcane categorization as the crop cycle includes large inconsistencies. Similarly, randomness in the time sequence paradigm might appear in the initial harvest, since the agriculturalist might cultivate other crops in similar fields. Yield maps become necessary to better comprehend the in-field changeability, for delimiting management regions, and enhance site-specific management techniques [8]. Sugarcane yield map can be generally gained from data accumulated straight by screens on harvesters that provide certain restrictions. An alternative typical feature of the prior study was the dependence on a single image at a presented crop phase for investigating the relation between yield and spectral Vis [9]. Assumed the comparatively advanced temporal resolution of accessible images (for instance, the revisit frequency of the Sentinel-2 constellation is 5 days), and the potentiality of new analytical tools for managing several variable forecasters, a time series method for sugarcane yield prediction was valuable to examine. Machine Learning (ML) methods were displayed to offer higher forecasting accuracy than the conventional statistical studies along with that identifying dataset patterns [10]. Such methods were typically imperilled to tests and training procedures, depending on the dataset difficulty.

In this study, we propose an Optimal Deep Learning Driven Smart Sugarcane Crop Monitoring (ODLD-SSCM) model on Remote Sensing Images. The presented ODLD-SSCM model mainly intends to estimate the crop yield of sugarcanes using RSIs. In the presented ODLD-SSCM technique, the sugarcane yield mapping can be derived by the use of the self-attentive deep learning (SADL) model. Besides, an oppositional spider colony optimization (OSCO) algorithm is used for the hyperparameter tuning of the ODLD-SSCM model. A detailed set of experimentations were performed to demonstrate the enhanced outcomes of the ODLD-SSCM model.

2. Related Works

Kumpala et al. [11] applied the DL technique depends on the CNN model YOLO which creates a simulation for recognizing images. The technique has been utilized for recognizing sugar cane diseases with specific images. The Sugar cane-Leaf Disease Diagnoses Scheme was developed and designed to assist the user in automatically recognizing sugar cane diseases. Sugar cane-Leaf Disease Diagnoses Scheme contained two: disease diagnoses and detection. The authors in [12], applied DL and computer vision technologies for selecting and planting healthier billets that improved the plant population and the yields for each hectare of sugarcane planting. The researchers applied popular CNN architecture for processing larger image datasets and TL approaches for expanding the outcomes to distinct types of sugarcane. It is time consuming to label and collects enormous datasets for every type of sugarcane where quality inspection is required, previous to planting. The author applied a two-step TL approach for extending the trained structure to novel variety.

In [13], proposed an object detection technique based on DL for sugarcane stem node detection in complicated environments, and the generalization and robustness capability have been enhanced using the dataset expansion model for stimulating distinct illumination conditions. The effect of data extension and lighting conditions in distinct times on the outcomes of sugarcane stem node recognition has been deliberated, and the dominance of YOLO v4 implemented best in the study has been confirmed by relating four distinct DL approaches such as YOLO v3, Fast RCNN, SSD300, and RetinaNet. Picoli et al. [14] examine the Landsat image probable for sugarcane scarcity recognition by measuring the relationships among normalized difference water index (NDWI), vegetation condition index (VCI), normalized difference infrared index (NDII), global vegetation moisture index (GVMI), agricultural and vegetation scarcity indices (normalized difference vegetation index (NDVI)). The study presented two novel indices merging short-wave infrared (SWIR) and near-infrared (NIR) bands projected for detecting sugarcane deficiency. Each index was collectively and individually compared to soil water surplus and water deficit, based on the climatological soil–water balance (CSWB) technique.

A new DL architecture has been developed in [15] for detecting either a sugarcane plant is contaminated or not by examining its stem, color, leaves, and so on. The study encompasses three scenarios according to the distinct feature extractors such as VGG-19, Inception v3, and VGG-16. They are the pertained model where distinct classifications are trained. Johansen et al. [16] used a higher-spatial resolution GeoEye-1 satellite imagery and geographic object-based image analysis (GEOBIA) for 3 years to map damages of canegrub and developed two mapping techniques appropriate for risk mapping. These involved: (1) early separation of sugarcane block limitations; (2) subsequent omission and classification of harvested or fallow tracks, fields, and other non-sugarcane features within the block limits; (3) detection of possible canegrub-damaged regions with lower NDVI value and higher level of image textures within all the blocks; (4) the additional filtering of canegrub spoiled area to lower, medium, and higher probability; and (5) classification of risk.

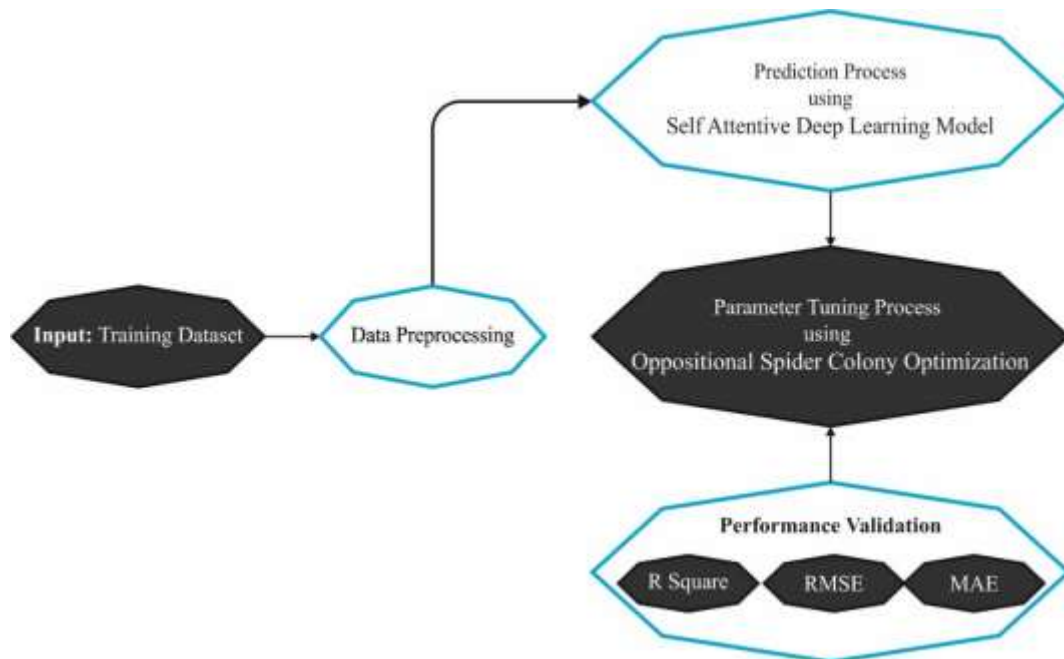


Figure 1: Block diagram of ODL-DSSCM approach

3. The Proposed Model

In this study, an effective ODL-D-SSCM model has been developed for smart sugarcane crop monitoring model on remote sensing images. The presented ODL-D-SSCM model mainly intends to estimate the crop yield of sugarcane using RSIs. In the presented ODL-D-SSCM technique, the sugarcane yield mapping can be derived by the use of the SADL model. Besides, the OSCO algorithm is used for the hyperparameter tuning of the ODL-D-SSCM model. Fig. 1 depicts the block diagram of the ODL-D-SSCM approach.

3.1 Yield Mapping Using SADL Model

In the presented ODL-D-SSCM technique, the sugarcane yield mapping can be derived by the use of the SADL model. The SADL integrates a self-attention module with the CNN for addressing the variable length signal data. Initially, convolution is used for the sensor signal for the feature extraction [17]. The sensor information is in the form of matrix with a sensor and variable length time axis. The matrix dataset of i -th wafer ($i = 1, \dots, N$) is denoted by $x_i = (x_i^{(1)}, \dots, x_i^{(T_i)}) \in \mathbb{R}^{D \times T_i}$, whereby D indicates the sensor count, and T_i indicates the timestamp count for the i -th wafer. For extracting correlation amongst each sensor, a convolution filter in the form of a non-square rectangle moves alongside the time axis. A convolutional filter w_k is employed to the raw sensor dataset with a window of F successive time steps for producing a feature map f_k .

$$H = (h^{(1)}, \dots, h^{(T-F+1)}) = (f_1, \dots, f_K)^T \quad (1)$$

Next, the variable-size matrix is encoded into a fixed-size vector. Rather than pooling the feature map across time, a self-attention module is presented for calculating the attention distribution $a^{(1)}, \dots, a^{(T-F+1)}$ which ignores irrelevant or noisy parts and focuses on relevant time steps.

$$a = (a^{(1)}, \dots, a^{(T-F+1)}) \quad (2)$$

$$= \text{soft max} (v_2^T \tanh (V_1 H)) . \quad (3)$$

Now, $V_1 \in \mathbb{R}^{S \times K}$ and $v_2 \in \mathbb{R}^S$ indicates weight matrixes and vectors, correspondingly, learned through BP. S indicates a hyperparameter signifying the hidden layer count and it is shown below.

$$h_o = aH = \sum_{t=1}^{T-F+1} a^{(t)} h^{(t)}. \quad (4)$$

The vector is a fixed-size encoder of variable-size H that summarizes the series with attention over time. Next, the feedforward layer is on top of the encoder to categorize the wafer stream for fault or normal classes. Attention weight has real benefits. It provides insight to determine the crop yield mapping of sugarcane. Fig. 2 illustrates the framework of the SADL technique.

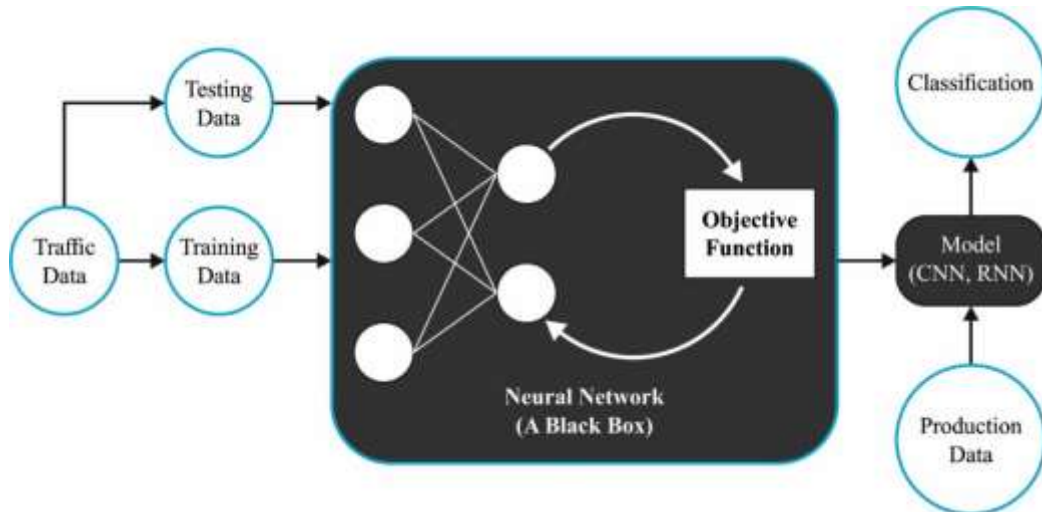


Figure 2: Structure of SADL**3.3 Parameter Tuning Using OSCO Algorithm**

Next, the OSCO algorithm is used for the hyperparameter tuning of the ODL-D-SSCM model. The SCO set the overall amount of spiders and arbitrarily assign individual of the male spider (MSP) groups, and marry the female spider (FSP) within the search space for generating novel spider individual and continues to repeat which realize the iteration of entire spider groups and continuously move close to the optimum solution [18], Lastly, the value of the optimum solution is attained and it is given below.

Initial value setting

The algorithm should set the first value of the number of FSP and MSP, for producing FSP and MSP population using the following equation

$$\begin{cases} N_f = [(0.9 - rand) \times 0.25] N \\ N_m = N - N_f \end{cases} \quad (5)$$

From the expression, the overall amount of spiders is N , 65%~90% of the Spider Population N is chosen as FSP, the remaining is MSP, N_f and N_m represent the number of male FSPs. F and M female and MSP sets are generated at random.

The following equation is used to define the r mating radius of the spider.

$$r = \sum_{j=1}^N (P_j^{high} - P_j^{low}) / 2N \quad (6)$$

Here, P_j^{high} and P_j^{low} indicates the upper and lower limits of j -dimension parameter.

Resolving the individual weight of the spider

The weight of an individual spider signifies its proportion while resolving the optimum solution and it is greater, then spider individuals are close to the optimum solution; if it is smaller, then spider individuals are distant from the optimum solution.

$$W_i = 1 - \frac{J(S_i) - worst}{best - worst} \quad (7)$$

Let W_i be the weights of individual spider, $J(S_i)$ shows the fitness values of all the individuals, $best$ and $worst$ indicate the fitness values of the best and worst individuals.

Female spider movement

The FSP gets closer to the individuals with large weight in the following:

$$F_i^{k+1} = \begin{cases} F_i^k + \alpha Vib_{ci}(S_c - F_i^k) + \beta Vib_{bi}(S_b - F_i^k) \\ + \delta(rand - 0.5), rand \leq PF \\ F_i^k - \alpha Vib_{ci}(S_c - F_i^k) - \beta Vib_{bi}(S_b - F_i^k) \\ + \delta(rand - 0.5), \end{cases} \quad (8)$$

$$Vib_{ij} = w_j e^{-d^2} ij \quad (9)$$

If $rand > PF$, the FSP iteration model is individual learning, farther from the neighborhood optimum individuals, far from the global optimum solution individual and random part, for ensuring the search accurateness. If $rand \leq PF$, the FSP iterative model is individual learning, closer to the neighborhood optimum individual, closer to the global optimum solution individual and random part.

Male spider movement

MSP mostly moves in two directions, one is attracted by individual females, and the rest is

closer to the middle MSP. The individual spider with the middle weight value is the middle MSP in the population as follows:

$$M_i^{k+1} = \begin{cases} M_i^k + \alpha Vib_{f_i} (S_f - M_i^k) + \delta(rand - 0.5), \\ W_{Nf+1} \geq W_{Nf+m} \\ M_i^k + \alpha_i \left(\frac{\sum_{h=1}^{Nm} M_h^k W_{Nf+h}}{\sum_{h=1}^{Nm} W_{Nf+h}} - M_i^k \right), Other \end{cases} \quad (10)$$

Now, W_{Nf+m} indicates the individual weight of middle MSP and s_f denotes the location of the individuals that weight is higher than the MSP i and closer to the MSP i . If $W_{Nf+1} < W_{Nf+m}$, the MSP iterative model is individual learning, closer to the middle male individuals. If $W_{Nf+1} \geq W_{Nf+m}$, the MSP iteration model is individual learning, closer to the optimum female individuals and random part in the neighborhood.

Male and female spider mating

For i -th individual males, within its r mating radius, if there exist female individuals, mating behavior occurs. A new spider is generated to form a novel Spider Population T_G after marriage. In the novel Spider Population T_G , evaluate the distribution probability of every individual:

$$PS_k = \frac{w_k}{\sum_{g \in T_G} w_g}, k \in T_G \quad (11)$$

The optimum individual S_{new} is chosen based on the probability roulette model. Once the location of the optimum individual S_{new} , optimum individual S_{new} replaces the worst. Iterate the abovementioned operation until each male and female could complete marriage.

The ODL-D-SSCM model is derived by the integration of SCO with the oppositional based learning (OBL) concept. This technique demonstrated to be an effective model to make the search pattern of metaheuristics more realistic [19]. This method stems from the instantaneous estimation of the opposite pair of the base agent to increase the probability of meeting matching agents. The conflicting of real number $N \in [j_L, j_U]$ is given as $\bar{N}$ in the following:

$$\bar{N} = j_L + j_U - N \quad (12)$$

In Eq. (12), j_L and j_U indicates the lower and upper bounds. In multi-dimension space, N is formulated by $N_k = \{N_{k1}, N_{k2}, N_{k3}, \dots, N_{kt}\}$ and $N_{kt} \in [j_{Lt}, j_{Ut}]$, whereas $t = 1, 2, 3, 4, \dots, n$ and it is shown below:

$$\bar{N} = \{\bar{N}_{k1}, \bar{N}_{k2}, \bar{N}_{k3}, \dots, \bar{N}_{kt}\} \\ \bar{N}_{kt} = j_{Lt} + j_{Ut} - N_{kt} \quad (13)$$

In the process of optimization, $\bar{N}$ the opposite point is replaced with the N solution according to the optimal fitness values. In another word, the location of the population is upgraded according to the $\bar{N}$ and N finest values.

4. Results and Discussion

This section investigates the experimental validation of the ODL-D-SSCM model under diverse aspects.

Table 1: Result analysis of ODL-D-SSCM approach with distinct measures

Variables	Dataset	RMSE	R2	MAE
Spectral	Training	1.52	0.975	1.034

bands				
	Testing	4.56	0.680	3.019
GNDVI	Entire	2.93	0.909	1.607
	Training	2.17	0.927	1.385
	Testing	5.36	0.592	3.909
NDRE	Entire	3.63	0.833	2.290
	Training	1.83	0.925	1.455
	Testing	4.61	0.591	3.667
NDVI	Entire	3.41	0.814	2.068
	Training	1.79	0.952	1.387
	Testing	4.73	0.620	3.726
WDRVI	Entire	3.32	0.810	2.266
	Training	2.26	0.976	1.346
	Testing	4.86	0.588	3.867
	Entire	3.68	0.812	2.280

Tab. 1 provides an overall yield mapping outcomes of the ODL-D-SSCM model. Fig. 3 offers a brief sugarcane yield mapping performance of the ODL-D-SSCM model on the spectral band. On training data, the ODL-D-SSCM model has offered RMSE of 1.52, R2 of 0.975, and MAE of 1.034. In addition, on testing data, the ODL-D-SSCM method has presented RMSE of 4.56, R2 of 0.680, and MAE of 3.019. Moreover, on the entire data, the ODL-D-SSCM technique has presented RMSE of 2.93, R2 of 0.909, and MAE of 1.607.

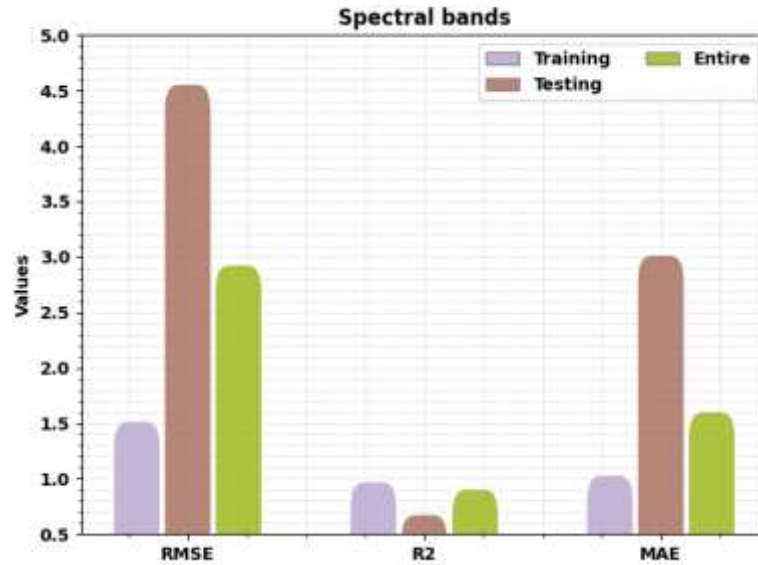


Figure 3: Result analysis of ODL-D-SSCM approach under Spectral bands

Fig. 4 provides a brief sugarcane yield mapping performance of the ODL-D-SSCM approaches on GNDVI. On training data, the ODL-D-SSCM technique has provided RMSE of 2.17, R2 of 0.927, and MAE of 1.385. Likewise, on testing data, the ODL-D-SSCM method has rendered RMSE of 5.36, R2 of 0.592, and MAE of 3.909. Also, on the entire data, the ODL-D-SSCM model has provided RMSE of 3.63, R2 of 0.833, and MAE of 2.290.

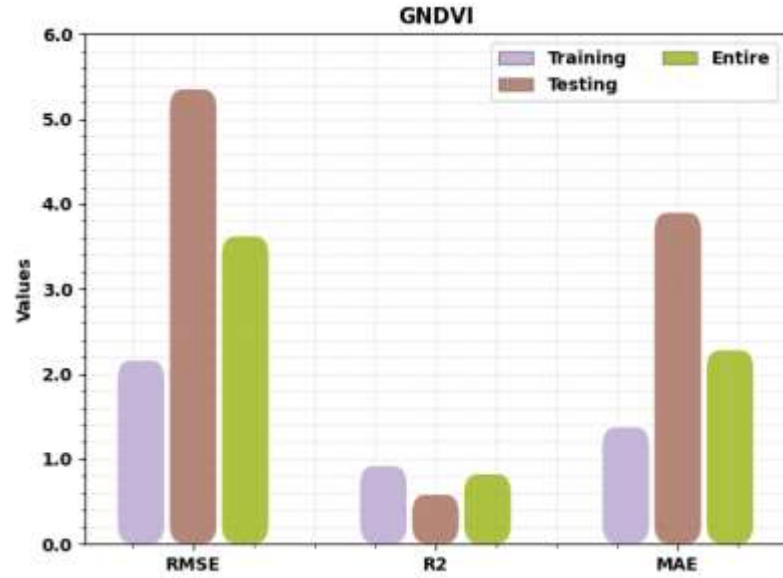


Figure 4: Result analysis of ODL-D-SSCM approach under GNDVI

Fig. 5 provides a brief sugarcane yield mapping performance of the ODL-D-SSCM approach on NDRE. On training data, the ODL-D-SSCM algorithm has presented RMSE of 1.83, R2 of 0.925, and MAE of 1.455. Similarly, on testing data, the ODL-D-SSCM method has offered RMSE of 4.61, R2 of 0.591, and MAE of 3.667. Additionally, on the entire data, the ODL-D-SSCM algorithm has rendered RMSE of 3.41, R2 of 0.814, and MAE of 2.068.

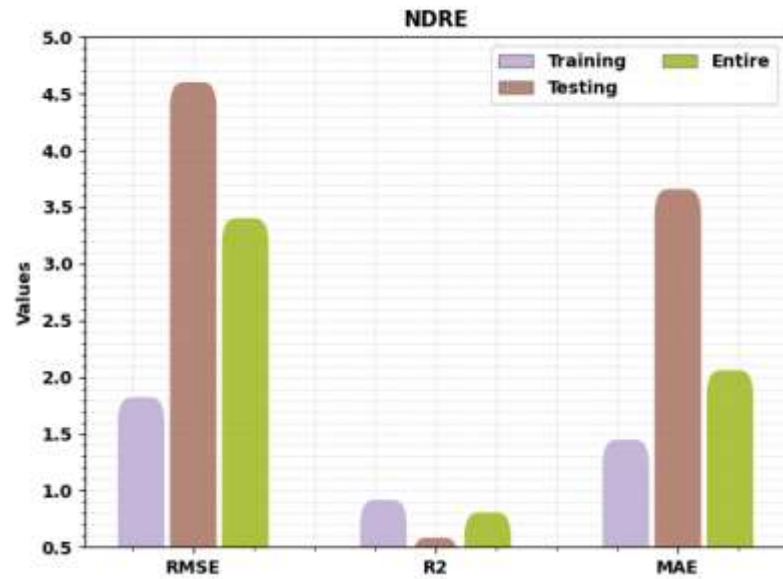


Figure 5: Result analysis of ODL-D-SSCM approach under NDRE

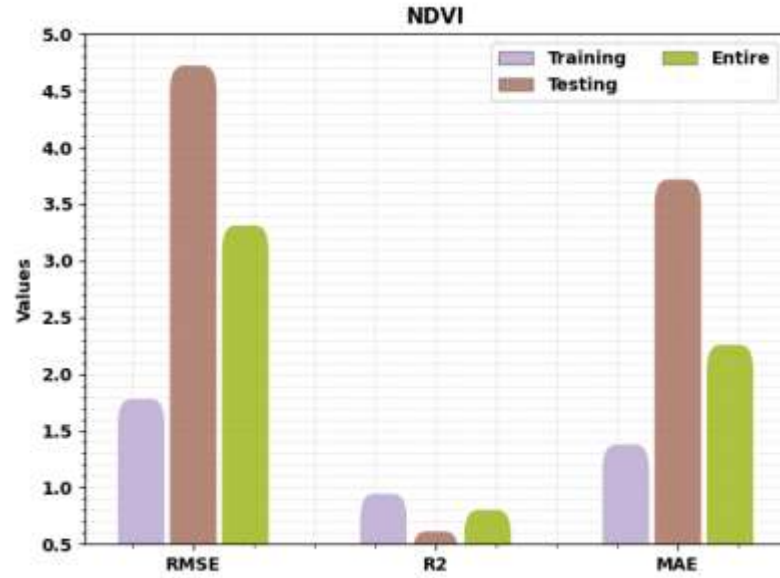


Figure 6: Result analysis of ODL D-SSCM approach under NDVI

Fig. 6 displays the detailed sugarcane yield mapping performance of the ODL D-SSCM model on NDVI. On training data, the ODL D-SSCM approach has offered RMSE of 1.79, R2 of 0.952, and MAE of 1.387. Also, on testing data, the ODL D-SSCM method has offered RMSE of 4.73, R2 of 0.620, and MAE of 3.726. Also, on the entire data, the ODL D-SSCM approach has offered RMSE of 3.32, R2 of 0.810, and MAE of 2.266.

Fig. 7 exemplifies a comprehensive sugarcane yield mapping performance of the ODL D-SSCM model on WDRVI. On training data, the ODL D-SSCM technique has provided RMSE of 2.26, R2 of 0.976, and MAE of 1.346. Also, on testing data, the ODL D-SSCM model has offered RMSE of 4.86, R2 of 0.588, and MAE of 3.867. Moreover, on the entire data, the ODL D-SSCM algorithm has rendered RMSE of 3.68, R2 of 0.812, and MAE of 2.280.

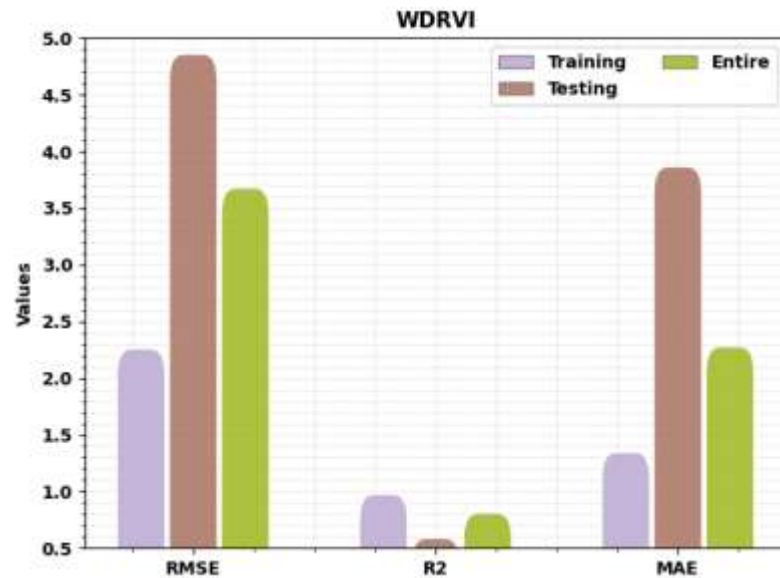


Figure 7: Result analysis of ODL D-SSCM approach under WDRVI

Tab. 2 and Fig. 8 provide a detailed RMSE examination of the ODL D-SSCM model with other

models on different bands [4]. The results indicated that the ODL-D-SSCM model has offered enhanced performance with the least RMSE values over other models. For instance, on the entire spectral band dataset, the ODL-D-SSCM model has offered a reduced RMSE of 2.93 whereas the RF and MLR models have gained increased RMSE of 3.35 and 6.34 respectively. Meanwhile, on the entire GNDVI dataset, the ODL-D-SSCM technique has presented a reduced RMSE of 3.63 whereas the RF and MLR algorithms have attained increased RMSE of 3.96 and 6.08 correspondingly. Finally, on the entire NDRE dataset, the ODL-D-SSCM algorithm has granted a reduced RMSE of 3.41 whereas the RF and MLR approaches have gained increased RMSE of 3.72 and 6.3 correspondingly. At last, on the entire NDVI dataset, the ODL-D-SSCM model has provided a reduced RMSE of 3.32 whereas the RF and MLR approaches have gained increased RMSE of 3.63 and 6.29 correspondingly.

Table 2: RMSE analysis of ODL-D-SSCM approach with existing algorithms under distinct bands

RMSE				
Variables	Dataset	Random Forest	Multiple Linear Regression	ODLD-SSCM
Spectral bands	Training	1.94	5.88	1.52
	Testing	4.88	6.23	4.56
	Entire	3.35	6.34	2.93
GNDVI	Training	2.56	6.35	2.17
	Testing	5.75	6.43	5.36
	Entire	3.96	6.08	3.63
NDRE	Training	2.16	6.39	1.83
	Testing	5.01	6.24	4.61
	Entire	3.72	6.3	3.41
NDVI	Training	2.27	6.68	1.79
	Testing	5.1	6.13	4.73
	Entire	3.63	6.29	3.32
WDRVI	Training	2.62	6.48	2.26
	Testing	5.27	6.15	4.86
	Entire	4.03	6.36	3.68

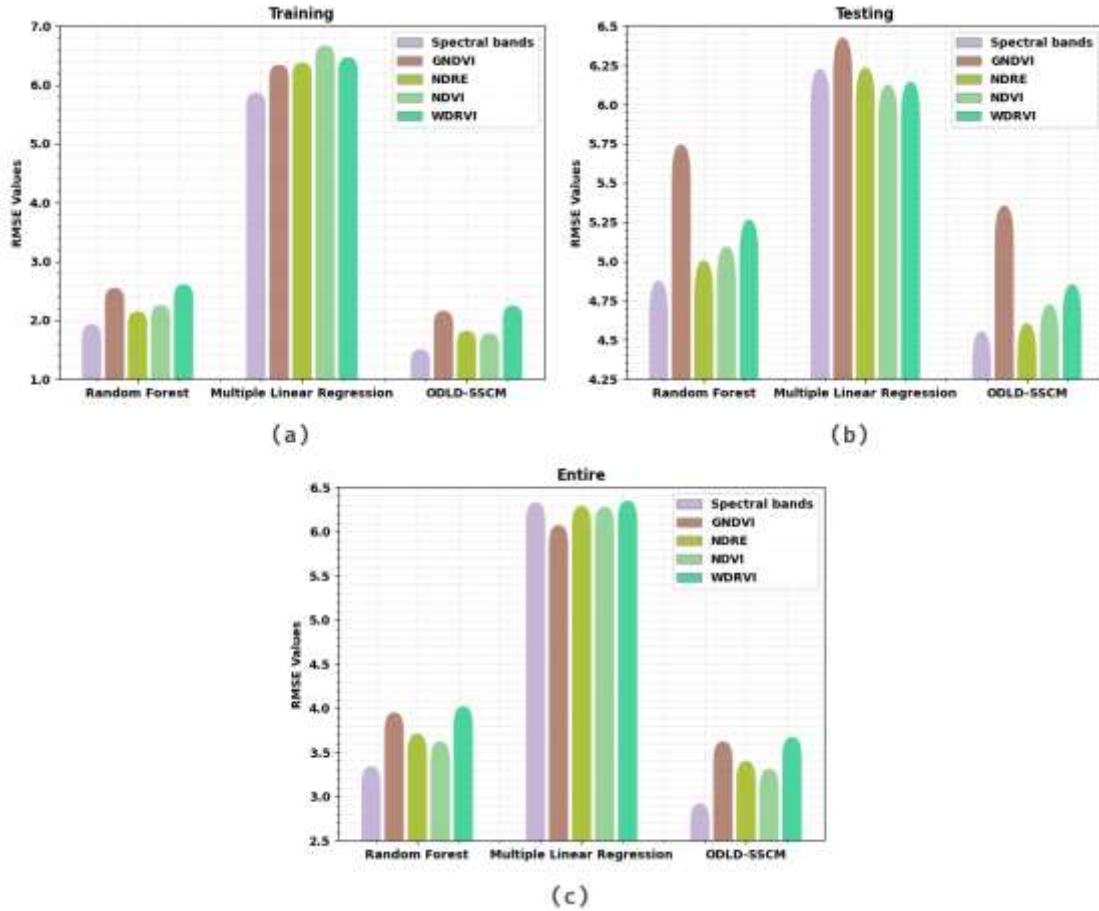
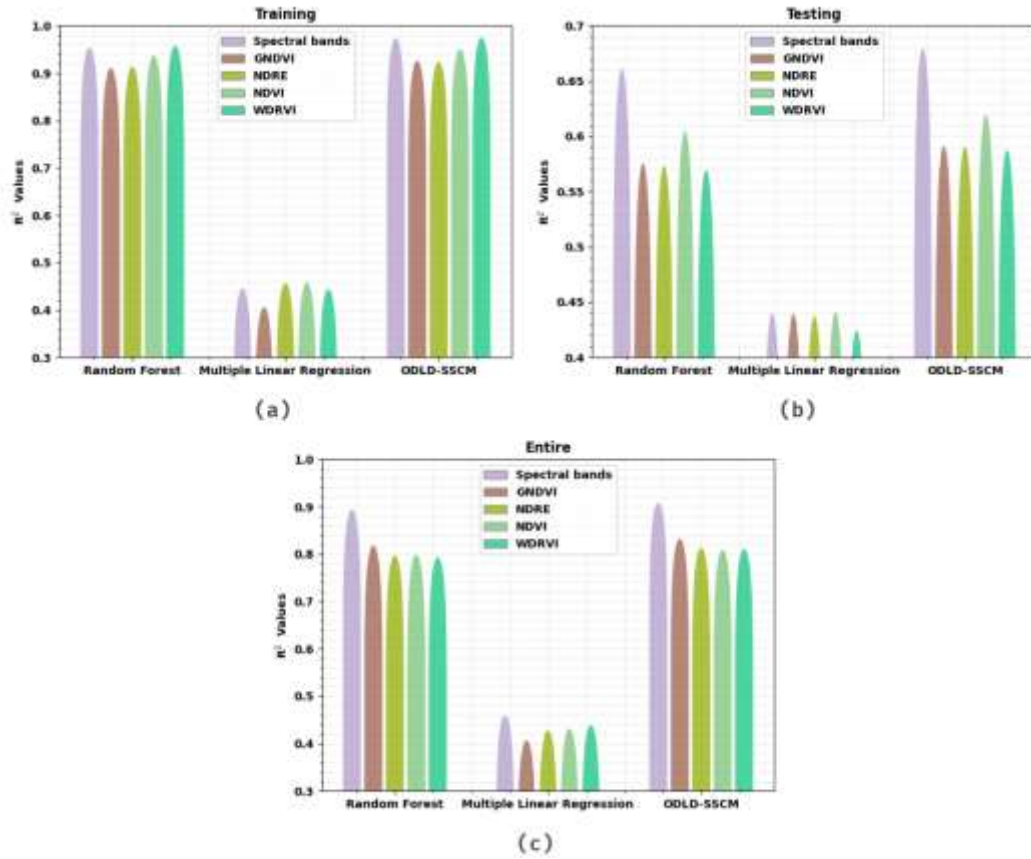


Figure 8: RMSE analysis of ODL D-SSCM approach (a) Training, (b) Testing, and (c) Entire

An extensive R^2 examination of the ODL D-SSCM model with recent approaches is provided in Fig. 9 and Tab. 3. The experimentation outcomes depicted that the ODL D-SSCM model has shown effectual outcomes with maximum R^2 values. For instance, on the entire spectral band dataset, the ODL D-SSCM model has accomplished a higher R^2 value of 0.909 whereas the RF and MLR models have demonstrated lower R^2 values of 0.895 and 0.461 respectively. Furthermore, on the entire GNDVI dataset, the ODL D-SSCM method has accomplished a higher R^2 value of 0.833 whereas the RF and MLR approaches have demonstrated lower R^2 values of 0.819 and 0.408 correspondingly. Additionally, on the entire NDRE dataset, the ODL D-SSCM technique has accomplished a higher R^2 value of 0.814 whereas the RF and MLR methods have demonstrated lower R^2 values of 0.798 and 0.429 correspondingly.

**Figure 9:** R2 analysis of ODLD-SSCM approach (a) Training, (b) Testing, and (c) Entire**Table 3:** R2 analysis of ODLD-SSCM approach with existing algorithms under distinct bands

R2				
Variables	Dataset	Random Forest	Multiple Linear Regression	ODLD-SSCM
Spectral bands	Training	0.955	0.447	0.975
	Testing	0.662	0.441	0.680
	Entire	0.895	0.461	0.909
GNDVI	Training	0.912	0.407	0.927
	Testing	0.576	0.440	0.592
	Entire	0.819	0.408	0.833
NDRE	Training	0.915	0.458	0.925
	Testing	0.574	0.438	0.591
	Entire	0.798	0.429	0.814
NDVI	Training	0.938	0.459	0.952
	Testing	0.605	0.442	0.620
	Entire	0.800	0.433	0.810

WDRVI	Training	0.959	0.445	0.976
	Testing	0.570	0.425	0.588
	Entire	0.794	0.440	0.812

Tab. 4 and Fig. 10 deliver a detailed MAE inspection of the ODL-D-SSCM method with other approaches on different bands. The results denote the ODL-D-SSCM approach has gained enhanced performance with the least RMSE values over other models. For example, on the entire spectral band dataset, the ODL-D-SSCM model has offered a reduced MAE of 1.607 whereas the RF and MLR approaches have obtained increased MAE of 2.077 and 4.692 respectively. Meanwhile, on the entire GNDVI dataset, the ODL-D-SSCM method has presented a reduced MAE of 2.290 whereas the RF and MLR approaches have obtained increased MAE of 4.838 and 2.660 correspondingly.

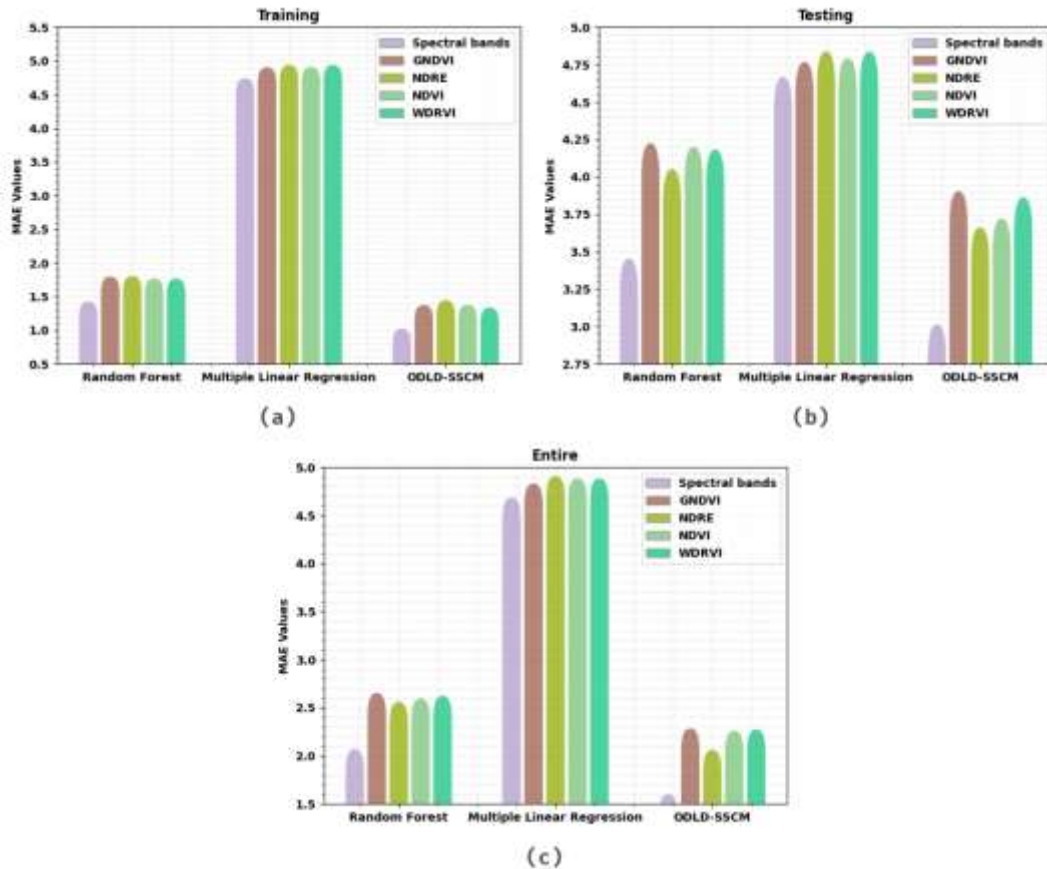


Figure 10: MAE analysis of ODL-D-SSCM approach (a) Training, (b) Testing, and (c) Entire

Table 4: MAE analysis of ODL-D-SSCM approach with existing algorithms under distinct bands

MAE				
Variables	Dataset	Random Forest	Multiple Linear Regression	ODL-D-SSCM
Spectral bands	Training	1.434	4.751	1.034
	Testing	3.459	4.672	3.019

GNDVI	Entire	2.077	4.692	1.607
	Training	1.805	4.914	1.385
	Testing	4.229	4.773	3.909
NDRE	Entire	2.660	4.838	2.290
	Training	1.815	4.951	1.455
	Testing	4.057	4.843	3.667
NDVI	Entire	2.568	4.916	2.068
	Training	1.777	4.920	1.387
	Testing	4.206	4.797	3.726
WDRVI	Entire	2.606	4.893	2.266
	Training	1.776	4.950	1.346
	Testing	4.187	4.840	3.867
	Entire	2.630	4.889	2.280

Eventually, on the entire NDRE dataset, the ODL-D-SSCM model has offered a reduced MAE of 2.068 whereas the RF and MLR techniques have obtained increased MAE of 2.568 and 4.916 correspondingly. Finally, on the entire NDVI dataset, the ODL-D-SSCM approach has provided a reduced MAE of 2.266 whereas the RF and MLR techniques have attained increased RMSE of 2.606 and 4.893 correspondingly. After examining these experimentation outcomes, the ODL-D-SSCM model ensured its betterment in sugarcane yield mapping performance over other models.

5. 5 Conclusion

In this study, an effective ODL-D-SSCM model has been developed for the smart sugarcane crop monitoring model on remote sensing images. The presented ODL-D-SSCM model mainly intends to estimate the crop yield of sugarcanes using RSIs. In the presented ODL-D-SSCM technique, the sugarcane yield mapping can be derived by the use of the SADL model. Besides, the OSCO algorithm is used for the hyperparameter tuning of the ODL-D-SSCM model which is derived by the integration of SCO with the OBL concept. A detailed set of experimentations were performed to demonstrate the enhanced outcomes of the ODL-D-SSCM model. A comprehensive comparison study pointed out the enhancements of the ODL-D-SSCM model over other recent approaches.

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