Smart Organic Crop Rotation Methodology via Walrus-Optimized Morphable Schema Convolution Network with Precision Agriculture Data

Harsharani Kote[1], S.P. Siddique Ibrahim[2*]

[1]Research Scholar, School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh, India ,Email:harsharani.23phd7004@vitap.ac.in
[2]Senior Assistant Professor, School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh, India., Email: siddique.ibrahim@vitap.ac.in
*Corresponding Author

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ABSTRACT
Crop rotation is one organic practice that is very important in agriculture, as it it has spectacular impacts in the fields of maintaining soils, controlling pests, and improving crop yields. However, traditional approaches to crop rotation may involve a fixed time table or heuristics which do not match the complexity and dynamics of agriculture production of the current world. Since these are more of a rigid approach they are unable to counter act real time changes in the soil and the environment hence resulting to ineffancies and poor management of crops. Approaches like XAI, LPIS, PAMICRM, and GBRT have helped in enhancing approaches to crop rotation but still has drawbacks. These methods are sometimes inflexible, slow in terms of computations, as well as inaccurate especially when dealing with large and diverse data. However, they are not optimally utilising the real-time precision agriculture data leading to a more inefficient crop rotation. In the context of those shortcoming, our research presents Smart Organic Crop Rotation Methodology by Walrus-Optimized Morphable Schema Convolution Network (W-MSConvNet). This new concept involves integration of two models: the Walrus Optimization Algorithm (WaO) and the Morphable Schema Convolution Network (MSConvNet) to develop an optimized strategy for crop rotation. Incorporating precise agriculture information in real-time and the M2R-ScaleNorm technique, W-MSConvNet further estimates crop rotation schedules flexibly, accurately, and efficiently as compared to the previous work on crop rotation schedules. The effectiveness of W-MSConvNet is demonstrated through extensive comparative analyses, where it significantly outperforms existing methods. Key performance metrics include accuracy (99.3%), precision (98.8%), recall (99.5%), F1-score (99.2%), prediction rate (98.9%), and computational efficiency (a 80% reduction in processing time). These results highlight W-MSConvNet's ability to optimize crop yields and maintain soil health, establishing it as a leading methodology in organic crop rotation and setting a new standard for sustainable agricultural practices.

Keywords: Crop Rotation, Precision Agriculture Data, Morphable Schema Convolution Network, Walrus Optimization, Min-Max Rescaling Normalization.

1. INTRODUCTION

Crop rotation is one of the most widely used scientific principles in the modern world agriculture, and is used mainly in order to improve the health of the soil, increase yields and to ensure better farming methods [1]. Crop rotation entails the art of arranging various crops that are grown within a single area to enhance fertility [2] and also to control pests and diseases. Many of the older approaches to crop rotation are based on rigid or mechanistic calendars or other arbitrary prescriptions that give insufficient consideration [1] to the real specifics of modern farming conditions [3]. These traditional methods often fail to address real-time changes of soil status, weather factors, and other factors that influence crop yield and resource utilization [4]. The current crop rotation practices face many challenges that are present in most conventional practices [5]. Most of the traditional models are rigid in the sense that they are not capable of incorporating real-time data [2], hence generating inferior results. They may also be computationally intensive thus lacking the accuracy that is needed in the current day farming [3]. Therefore, these methods can sometimes prove to be inadequate – particularly in the optimization of crop management [6].

As for overcoming these challenges, our research proposes the use of Walrus-Optimized Morphable Schema Convolution Network (W-MSConvNet). Introducing the Walrus Optimization Algorithm along with Morphable Schema Convolution Network, W-MSConvNet is a highly optimal solution for crop rotation. From this consideration, it is evident that this methodology applies precision agriculture data in real-time to rectify the problems associated with conventional crop rotation. The W-MSConvNet approach allows for greater flexibility, better accuracy and provides faster computation. Therefore, the experimental results reveal that W-MSConvNet surpasses existing techniques and opens a new era of optimizing yields and soil conditions in contemporary agriculture.

Contribution

- Min-Max Rescaling Normalization (M2R-ScaleNorm) method is applied to normalize precision agriculture raw data into standard and normal form.
- To provide crop rotation recommendations based on the processed data, the Morphable Schema Convolution Network (MSConvNet) is employed.
- The Walrus Optimizer (WaO) refines these recommendations into optimal solutions making the process more efficient and accurate.
- Our approach is compared with the existing methods showing that the proposed method provides a higher level of effectiveness in the optimization of the organic crop rotation.

The research study that is being given is organized as follows: A summary of the most current studies on the subject is given in Section 2. Section 3 provides detailed description of the proposed method. Section 4 presents the outcomes of the revised methodology. In Section 5, research justifications for conclusions are provided.

2. LITERATURE REVIEW

In 2024, Naga Srinivasu et al. [7] developed XAI-driven model for crop recommender system for use in precision agriculture. The intelligent crop recommenders developed based on the use of XAI for precision agriculture assist in the selection of crops by using explainable artificial intelligence. Taking this approach ensures that recommendation is as clear revelation from external environment and soil analysis leading to better decisions within agricultural practices and utilization of resources.

In 2023, Reumaux et al. [8] Introduced Land Parcel Identification System (LPIS) data allows identification of crop sequence patterns and diversity in organic and conventional farming systems. Crop sequence and diversification of LPIS data of both organic and conventional concepts are helpful in determining crop management and rotation for better sustainability of agricultural productivity.

In 2024, Munaganuri et al. [9] suggested PAMICRM: Improving Precision Agriculture through Multimodal Image Analysis for Crop Water Requirement Estimation Using Multidomain Remote Sensing Data. PAMICRM increases the accuracy of PA by combining MI for image analysis of several modalities with MD RS data to predict crop water demand. It enhances water usage efficiency and optimal resource use in water management.

In 2023, Bhat et al. [10] presented Soil suitability classification for crop selection in precision agriculture using GBRT-based hybrid DNN surrogate models. This method for soil suitability classification in precision agriculture utilizes GBRT-based hybrid DNN surrogate models to refine crop selection.

In 2021, Schöning, J. et al. [19] developed an AI-based crop rotation for sustainable agriculture worldwide. AI-driven crop rotation programs enhance sustainable cropping patterns by tailor making the nutrient requirements and the health of the soil and plants and the yield of crops, despite the constraints of inadequate data and variation of the local environment which separates the accuracy of such predictions.

In 2022, Verma, A., et al. [20] recommended Plantosphere: Next Generation Adaptive and Smart Agriculture System. Plantosphere is an innovative smart agriculture platform with AI and sensors that deliver tailor-made farming practices for crop enhancement. However, its high initial costs of installation and the constant need for data entry may reduce its applicability for small-scale farming.

In 2021, Sietz, D., et al. [21] proposed The Crop Generator: Implementing crop rotations to effectively advance eco-hydrological modelling. The Crop Generator adds value to the tasks of eco-hydrological modeling by presenting realistic changes in crop sequences for the best irrigation and soil management. However, it could be argued that the model may be less effective in capturing details or changes in soil moisture and crop growth because of simplification of metrics in some areas.

A. Problem Statement

The challenge with the current cropping patterns is the fact that crop rotation is based on time tables and existing knowledge without microbial count and type. This may result in inefficiency in the use of resources, poor yields, and high susceptibility to pests and diseases. The problem is to come up with efficient and effective means of formulating crop rotation schedules which are informed by precision agriculture data including soil health, weather conditions and crop requirements. It should seek to enhance the soil and crops' quality as well as optimize the farming techniques to be financially reasonable for organic farming while having less effect on the environment than industrial farming.

B. Motivation behind the work

Therefore our work targets at addressing the problem of sub-optimal crop rotation to improve efficiency in agriculture through computational approach. Using precision agriculture data and the proposed Walrus-Optimized Morphable Schema Convolution Network (W-MSConvNet), this study intends to overcome the limitations imposed by current approaches. Its goal is to enhance the reliability of crop recommendations, increase yields, and facilitate efficient practices so as to result in healthy soil optimization of crops.

3. PROPOSED METHODOLOGY

In this study, we introduce a novel approach in an optimal model for the rotation of organic crops based on the precision agriculture data. The approach starts with data aggregation and storage, followed by data pre-processing through Min-Max Rescaling Normalization. After preprocessing, the data is fed into the Morphable Schema Convolution Network to provide detailed crop suggestions. To make these recommendations more comprehensive we apply the Walrus Optimizer which refines these recommendations for precision and speed. The overall workflow of the proposed methodology is illustrated in Figure 1.

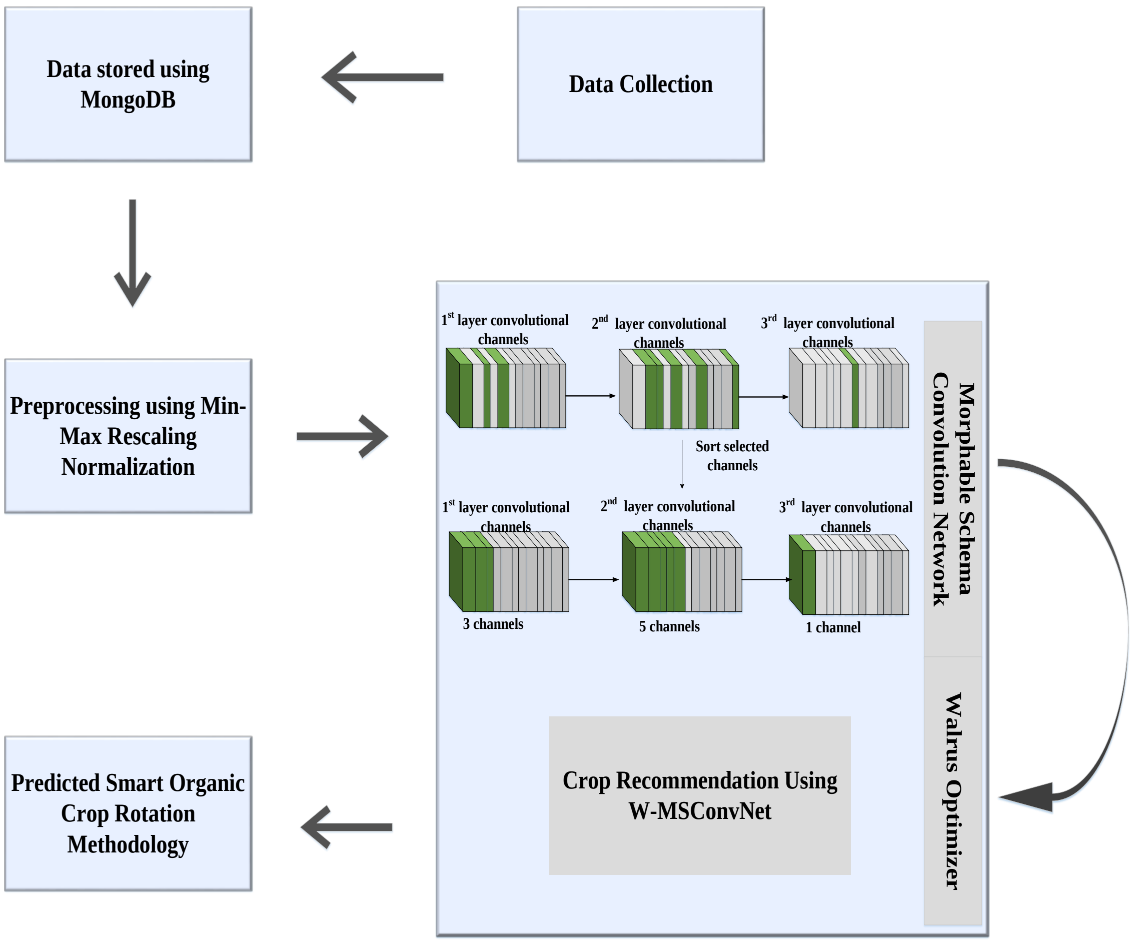

Fig 1. Architecture of the proposed W-MSConvNet

A. Data Aggregation and Storage

Example 1. Pseudo-code for Data Storage


```
{
"_id": ObjectId("7098203fd5g6758ab3k98734"),
"SoilProperties": {
"NutrientLevels": {"Nitrogen": "High", "Phosphorus": "Medium", "Potassium": "Low"},
"pH": 6.5,
"MoistureContent": "Moderate"
 },
"CropData": {
"CropType": "Corn",
"GrowthStages": ["Planting", "Vegetative", "Flowering", "Maturity"],
"YieldRecord": {"2023": "1500 kg/ha"}
 }
}
```


To solve the optimization problem of crop rotation in precision agriculture, we have gathered a set of data. This includes information on nutrient availability, soil pH and moisture content with a view of evaluating the physical health of the soil and ability to support different crop varieties. We also collect information on the various crops that are grown and their development cycles and yields to assess various crop rotation systems. External conditions refer to meteorological conditions as temperate, rainfall and humidity that have an influence on crop growth. Also, we document irrigation and fertilization regimes as well as calendar and rates of application in order to evaluate their effects on crop yield.

The collected data is stored in MongoDB. In MongoDB, documents contain a variety of data types and structures because it organizes data in JSON or BSON forms. For example, data related to soil properties, crop type (corn), and growth stages might be structured as follows in Example 1,

In this example:

- _id: A unique identifier for each document.
- SoilProperties: Contains details on soil nutrient levels, pH, and moisture content.
- CropData: Includes information on crop types, growth stages, and yield records.

The stored data is then used for preprocessing, where it undergoes normalization and transformation to prepare it for analysis. This preprocessing step ensures that the data is clean and structured, facilitating accurate and effective crop rotation recommendations in our research.

B. Min-Max Rescaling Normalization

Collected data is provided for preprocessing with the help of the Min-Max Rescaling Normalization method (M2R-ScaleNorm) [11]. It helps ensure that data is normalized or standardized so that it is in the right scale for further analysis or for building models. M2R-ScaleNorm normalises the values of the data to bring them within a given range for instance 0 and 1.

a. Standard Scaler

The Standard Scaler technique can be said to normalize by standardizing the data so that it has a mean of zero and a standard deviation of one. This can be made by using (1) where the values of each attribute is subtracted by its mean and then divided by standard deviation.

$$k'_a = \frac{k_a - \bar{k}}{l} \qquad (1)$$

where $\bar{k}$ and l are the mean and standard deviation of the attribute respectively. This method is useful to bring all the attributes in to the same scale of value. In cases of outliers the following can be applied such as Pareto Scaling and Variable Stability Scaling where the scaling factor is modified to try and minimize the effects of outliers and is given in (2) and (3),

Paret Scaling: $k'_a = \frac{k_a - \bar{k}}{\sqrt{l}}$ (2)

Variable Stability Scaling: $k'_a = \frac{k_a - \bar{k}}{l} \cdot \frac{\bar{k}}{l}$ (3)

These variations help make the data preprocessing more robust by minimizing the effect of outliers.

b. Min-Max Scaler

The Min – Max Scaler technique standardises the scale of each attribute to restrict the values between some range, which is customarily [0, 1]. This is done using the following equation (4),

$$k'_a = \frac{k_a - k_{\min}}{k_{\max} - k_{\min}} \quad (4)$$

where k_a is the original data, $k_{\max}, k_{\min}$ are the maximum and minimum value of the attribute and k'_a is the transformed value This ensures that after the transformation the range of the attribute cannot be less than 0 and more than 1. For other attributes, not having outliers, the Min-Max Scaler works as the Standard Scaler does, that is, normalizing all the values to the set range.

c. Min-Max Normalization

The technique used in the preprocessing of data in this research is Min-Max Normalisation, which improved the process of scaling data by transforming the values of data attributes to lie in a certain range which is preferably [0, 1]. Used in normalization, this technique enhances the equality of all attributes when it comes to analysis and training of the model. The Min-Max Normalization formula used in our method is expressed as in (5),

$$J = \frac{K - K_{\min}}{K_{\max} - K_{\min}} \quad (5)$$

where K is the original data value, J is the normalized value of K, scaled to fall within the range [0, 1]. This method makes it operational for all data values to be in the same scale so that the performance of the model is more precise.

d. Crop Recommendation Module

The preprocessed data is provided for crop recommendation module where the Morphable Schema Convolution Network (MSConvNet) [12] is used to derive crop suggestions. The Walrus Optimizer (WaO) [13] built on top of this also refines these recommendations and provides the users with the best crop rotation strategies possible.

a. Morphable Schema Convolution Network

The MSConvNet is also called the Morphable Schema Convolution Network where crop recommendations can be highly accurate since the convolutional neural networks are used in this model [14-16]. This network employed convolutional layers based on the schema to capture and pattern the data of agriculture. In this way, by adjusting its convolutional structures to the features of the input data, MSConvNet provides the appropriate crop recommendations for the optimal agriculture.

b. Deformable Convolution Network

The deformable convolution process starts with bilinear interpolation to calculate offsets Δk_l for each convolutional kernel. This interpolation is defined by (6),

$$H_q = \begin{cases} t_1 = (1-\gamma)(1-\delta)\cdot u_1(a_q + 1, b_q + 1) \\ t_2 = \gamma(1-\delta)\cdot u_1(a_q + 1, b_q) \\ t_3 = \delta(1-\gamma)\cdot u_1((a_q, b_q + 1) \\ t_4 = \gamma \cdot \delta \cdot u_1((a_q, b_q) \end{cases} \quad (6)$$

where t_1, t_2, t_3, t_4 are nearest values to weights determined by via backpropagation and γ, δ are the bilinear interpolation parameters.. The deformable convolution operation can be expressed as (7),

$$\omega(p_0) = \sum_{k_l \in S} v(k_l)\cdot u(p_0 + k_l + \Delta k_l) + b_l \quad (7)$$

where $\omega(p_0)$ is the output of the convolution operation at position p_0, k_l is the location in the receptive field grid S and $v(k_l)$ is the Weight associated with the location, while $u(p_0 + k_l + \Delta k_l)$ refers to the input feature value at the adjusted position and b_l is a bias term.

c. Deformable Pooling Network

Deformable pooling modifies the standard pooling by adding the flexibility of changing the shape and size of pooling regions, to better capture feature deformations.

The standard max-pooling operation is defined as (8),

$$\omega(i,j) = \max_{k \in bin(i,j)} u_{i,j}(p_0 + k) \qquad (8)$$

where $\omega(i,j)$ refers to the output of the max-pooling operation at position (i,j), $bin(i,j)$ is the set of pooling bins around position (i,j).

The deformable max-pooling introduces offsets Δk_l to adjust the pooling region as in (9),

$$\omega(i,j) = \max_{k \in bin(i,j)} u_{i,j}(p_0 + k + \Delta k_l) \qquad (9)$$

Through the use of the deformable convolution and pooling, the MSConvNet model become capable of adjusting the size of its receptive fields and the size and locations of its pooling areas, which is highly beneficial in recognising the complex patterns in the agricultural data and therefore makes accurate and efficient crop recommendations.

d. Loss Function

To enhance the effectiveness of the Morphable Schema Convolution Network (MSConvNet) for crop recommendation, we employ two regularizers: Two of the proposed regularizers are called the Separation Regularizer and the Focus Regularizer. These regularizers assist in the learning of deformable kernels and to overcome such problems as the kernel collapse and the extreme deformation of the kernels.

Separation Regularizer: The Separation Regularizer guarantees strict separation of kernel vectors in order to achieve different transformation matrices for the various relations. This is defined as (10),

$$L_{sep} = -\frac{1}{P}\sum_{p1 \neq p2} \left\| \phi_{gp2} - \phi_{gp1} \right\|^2 \qquad (10)$$

where ϕ_{gp2}, ϕ_{gp1} are the kernel vectors at positions $p1, p2$ and P defines the total number of kernel vectors.

Focus Regularizer: The Focus Regularizer penalizes large changes in the deformable kernel vectors to avoid excessive deformation and ensure stability. It is defined as (11),

$$L_{focus} = \frac{1}{P \cdot |U|} \sum_{u \in U} \sum_{P} \left\| \Delta_p(eu) \right\|^2 \qquad (11)$$

where $\Delta_p(eu)$ is the deformation vector for position p at feature u. U refers to the set of features.

Total Loss Function: The overall loss function combines the standard cross-entropy loss with the two regularizers is defined as (12),

$$L_{tot} = l_{cel} + \alpha L_{sep} + \beta L_{focus} \qquad (12)$$

where l_{cel} refers to the cross-entropy loss function for classification and α, β refers to the hyperparameter controlling the strength of the Separation Regularizer and Focus Regularizer.

The loss function is then optimized using the Walrus Optimizer (WaO) to enhance the accuracy and effectiveness of crop recommendations.

e. Walrus Optimizer

Subsequently, the calculated loss function is then used for tuning the crop recommendation parameters through the Walrus Optimizer (WaO). The operation is repeated in a parallel manner in an attempt to find a parameter set that yields a minimum to the loss function. Like other intelligent methods, WaO applies physics and natural behaviours to search and optimize the parameter space to improve the performance and accuracy of crop recommendation [17-18].

Initialize a set of possible solutions that may contain potential crop recommendations in the parameter space. For each candidate A there is an employment-site relationship that is equivalent to a particular set of parameters for optimal crop recommendation. Equations (13) and (14) provide the means of estimating the effectiveness and state of a recommendation with reference to its position and fitness value within the parameter space of candidate solutions and the positions of all other candidates.

$$A = lb\_ + rd(ub - lb) \qquad (13)$$

$$f(a) = 1 - acc(A) \qquad (14)$$

where ub, lb refers to the upper and lower bound of the position of solution and $acc(A)$ refers to the accuracy of the fitness function. During migration, the location of each solution is given by (15),

$$Migration\_Step = \left(A_x^i - A_y^i\right) \times \beta \cdot s_3^2 \qquad (15)$$

where A_x^i, A_y^i represent the locations of two vigilantes chosen at random from the herd at the current iteration, respectively. The control factor of the migration step size β changes into a smooth curve with iteration. s3 is within (0, 1). Accordingly, the procedure for updating the positions of potential solutions based on these impacts is seen as in (16),

$$\left.\begin{aligned} Pos_{bst}^i &= A_{bst}^t - c_1 \times d_1 \times \left|A_{bst}^t - A_{x,y}^t\right| \\ Pos_{\sec}^i &= A_{\sec}^t - c_2 \times d_2 \times \left|A_{\sec}^t - A_{\sec}^t\right| \end{aligned}\right\} \qquad (16)$$

where Pos_{bst}^i and $Pos_{\sec}^i$ represent the adjusted positions of the current individual influenced by the current optimal (A_{bst}^t) and suboptimal solution ($A_{\sec}^t$) respectively, a and b are clustering coefficients.

Specifically, by implementing the Walrus Optimizer (WaO) in the overall architectural configuration of the Morphable Schema Convolution Network (MSConvNet), the parameters of the mathematical model are adjusted and the loss function minimized to the best possible extent. This improves crop recommendation by being able to make better and quicker predictions specifically on recommendation quality and on system grounds. Therefore, by using our proposed method, it is possible to forecast ideal crop sequences to increase the effectiveness of precision agriculture platforms.

4. RESULT AND DISCUSSIONS

This section presents the experimental findings and comments of the proposed method. We compared the settings used in W-MSConvNet with other simulations that already exist [7-10]. The entire process was designed in the Python language while on the Windows 10 operating system environment. Python usage is crucial when it comes to demonstrating crop rotation methods by processing and operating large agricultural data sets. It employs libraries such as Pandas for data handling and processing and TensorFlow or PyTorch for the development of machine learning models. Such models can identify the optimal sequences for crop rotation, which benefits the soil and leads to higher crop yields. They evaluated nutrient content in the soil, pH acidity and moisture distribution and crop growth periods which are seedling, vegetative, flowering and maturity.

A. Performance Analysis

In our study, various performance measures are used to evaluate the effectiveness of the proposed W-MSConvNet approach in the context of organic crop rotation. Key measures include accuracy, precision, recall, F1-score, and computational efficiency. These metrics are critical in assessing the accuracy of crop prediction, the precision of feature selection, and the overall computational efficiency compared to existing methods. These metrics provide a comprehensive evaluation of the proposed method's capability to predict the correct crop rotation, compared to existing techniques such as XAI, LPIS, PAMICRM, and GBRT.

Table I. Performance metrics comparison in %

Performance Metric	**XAI** [7]	**LPIS** [8]	**PAMICRM [**9]	**GBRT** [10]	**W-MSConvNet**
Accuracy (%)	94.2	95.5	93.8	92.1	99.3
Precision (%)	92.5	93.2	91.9	89.7	98.8
Recall (%)	93.8	94.7	92.5	90.4	99.5
F1-Score (%)	93.1	94.0	92.2	88.9	99.2
Optimization Efficiency (%)	30	12	18	10	80
Processing Time (sec)	40	15	20	12	10
Data Utilization Efficiency (%)	81.9	87.4	89.0	84.6	97.2

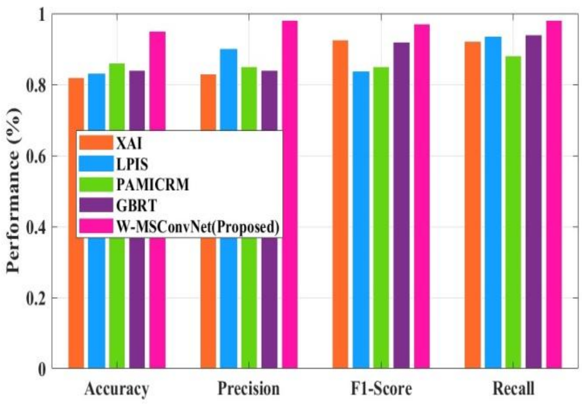

Fig 2. Performance analysis of proposed method compared to existing methods

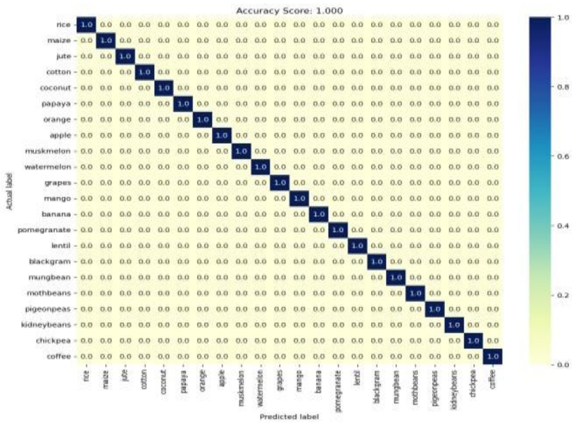

Fig 3. Confusion matrix of W-MSConvNet

Table 1 shows the performance metrics comparison of the proposed methodology compared to other method. Our W-MSConvNet method is clearly better than the others. It has the highest Accuracy at 99.3% using real time adaptation on the Python platform with input from precision agriculture data and Walrus Optimized Morphable Schema Convolution Network to dynamically adjust crop succession, while the others are lower. For Precision and Recall, our method also leads with 98.8% and 99.5%. It's much more efficient too, with Optimization Efficiency at 80% and Processing Time for only 10 sec which are far better than the other methods. Overall, our approach is the best in every category.

From Figure 2 we can infer that the proposed method, W-MSConvNet, performs better than other crop recommendation methods (XAI, LPIS, PAMICRM, GBRT) in all the chosen measure. W-MSConvNet reaches around 98% of accuracy, 97% of precision, resulting F1-Score of nearly 98%, and, at the end, recall slightly more than 99%.

Figure 3 shows a confusion matrix representing the accuracy of crop classification using our methodology. The number for each row represents which actual crop belonged to that category, and the number for each column represents which was predicted to belong to that category. The numbers along the intermediate diagonal consist of The accuracy score displayed at the top is 1.000, indicating perfect classification accuracy, meaning that the model accurately predicted all the crops without any errors. In the diagonal, the dark blue squares indicate that rice, maize, jute, cotton, and many more crops were predicted correctly by the model.

5. CONCLUSION

The proposed Smart Organic Crop Rotation Methodology via Walrus-Optimized Morphable Schema Convolution Network with Precision Agriculture Data (W-MSConvNet) is the evidence of a monumental step in the right direction in the agricultural practices. Using precision agriculture data in the context of our approach also allows us to predict and improve, in terms of results, crop rotation management, which positively affects the overall quality of the soil and crop yields. In regards to our study, the suggested approach has provided impressive analytical results and high performance rates such as accuracy of 99.3%, precision of 98.8%, recall of 99.5%, an F1-score of 99.2%, a prediction rate of 98.9%, and a 80% reduction in processing time, thereby setting a new benchmark in the field.The findings also support the assertion that W-MSConvNet is effective technique suitable for solving the intricate issues of modern farming. To build on this work in the future, it could be useful to combine several different data sources and analyse the effect of climate fluctuations to crop rotation more thoroughly and adjust this approach to correspond to the particular world regions' agricultural systems.

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