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A nutrient recommendation system for soil fertilization based on evolutionary computation

Usman Ahmed [a], Jerry Chun-Wei Lin [a,*], Gautam Srivastava [b,c], Youcef Djenouri [d]

[a] Department of Computer Science, Electrical Engineering and Mathematical Sciences, Western Norway University of Applied Sciences, Bergen, Norway
[b] Department of Mathematics and Computer Science, Brandon University, Brandon, Canada
[c] Research Center for Interneural Computing, China Medical University, Taichung, Taiwan
[d] Department of Mathematics and Cybernetics, SINTEF Digital, Oslo, Norway

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ABSTRACT

In agricultural production, soil characteristics play a vital role in maintaining fertility by allowing crops to develop better through root nutrition with minimal energy inputs. Nitrogen (N), Phosphorus (P), and Potassium (K) are all important nitrogen fertilizers extensively utilized in crops to supply a sufficient level of nutrients and keep their production level high. However, the application is generally limited to specific crops because of the global variability in these essential nutrients. Stability in fertilizer application, growth, and root growth rate increases crop fertility and crop production. To predict the suitable nutrients for different crops and provide nutrients recommendations by analyzing the crop fertility and yield production, this paper proposes nutrient recommendations through an improved genetic algorithm (IGA) that uses time-series sensor data and recommends various crop settings. A neighborhood-based strategy is then presented to handle exploration and exploitation for optimizing the parameters to obtain the maximum yield. The method can expand knowledge by using the population exploration strategy. The final recommendation is made by using the similarity between recommended patterns and real-time sensor data. With time, crop fertility decreases due to the low level of nutrients. This crop model will help to increase yield by analysis of the seasonal fertility performance of the soil. The proposed method is also a useful tool to improve soil fertility performance by providing the nutrient recommendation of optimal conditions for crop development. Experimental results show that the proposed model can recommend optimizing patterns and increasing the yearly yield efficiently. The method can help identify the region to assess crop suitability under certain nutrients levels and give insight into nutrient suitability assessments concerning specific crops in a climate-changing world.

1. Introduction

The agricultural industry plays an essential role in the growth of the entire economy of a country. The quality of soil is required to be maintained for the cultivation process. The utilization of intelligent technologies for planning, analysis, and production control are essential to improve the productivity of organic soil, plant nutrition, and quality of water of agriculture (Zamora-Izquierdo et al., 2019; Klerkx et al., 2019; Casta neda-Miranda and Casta no-Meneses, 2020). Fast improvements in the Internet of Things (IoT) (Lin et al., 2021), and cloud computing are pushing the marvel of what is called intelligent farming (Suchithra and Pai, 2020). Precision agriculture is an essential part of the durable intensity of agriculture, where information and communication technologies and other technologies are essential, but not enough for sustainable agricultural systems (Priya and Ramesh, 2018). Technology should fit into the practice of farmers and should be handled by their experienced-based and valuable knowledge to contribute to increasing sustainability in farming. Precision agriculture utilizes a remote sensor, which has improved dramatically due to innovative, sustainable, low-cost fertilizers and pesticides. One of the reasons for the improvement is the usage of information and communication technology (ICT). ICT is a network system that provides information on the conditions of production, process control, equipment, operations, and environment (Priya and Ramesh, 2018). With ICT usage, we can increase the efficiency of operation and management of farming with less cost and workforce for agriculture. The ICT utilizes the model

* Corresponding author.
E-mail address: jerrylin@ieee.org (J.C.-W. Lin).

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like crop growth production prediction, statistical learning methods, and decision support systems.

Another exciting aspect is that the usage of improper fertilizer results in nutrients (macro and micro) decline level imbalance. The lack of nutrients results in a decrease in yield production, automatically increasing the production cost. This also affects environmental costs at the same time for lack of nutrients in gaseous form. In a report (Zamora-Izquierdo et al., 2019; Priya and Ramesh, 2018), farmers in India are making use of soil at its maximum density, resulting in the cultivation of two crops a year without soil management methods. The method results in nutrient deficits over time and changes in the chemical structure of the soil. These can be taken because the soil becomes more susceptible to microbial contamination and lacks the quality of crops. With nitrogen imbalance, plants are not able to perform soil development activities. Therefore, a current need to ensure continuous monitoring of the soil with a well-understood approach to maintain a high soil organic matter level and nutrition abundance. A soil test for nutrients (including nitrogen and phosphorous) can be used before fertilization. In case of nutrient deficiency, recommended nutrients should be provided. In this way, yield production will be high, and soil fertility is maintained at a high level.

In (Priya and Ramesh, 2018), the authors have recognized the regional soil variation within different agricultural areas. The soil monitoring technique has also been developed with different crops being placed under different environmental conditions, e.g., using an essential nutrient for specific climate conditions. The discussed method helps increase plants' ability to grow with fertilizer and produce a high yield. It enhances productivity along with the usage of nutrients that have critical applications in soil engineering. GPS (global position system) helps access different soils, associated sensors, automatic hardware control, and irrigation system frameworks. Precision farming with GPS will give practical information for the optimal management of local environments and agriculture (Priya and Ramesh, 2018). This helps in the decision-making of the decision support system and application of water control and spraying drones.

Motivation: Soil is the most basic organic resource of the earth; it helps in food production and maintains the balance of local, global, and regional environmental quality. In Asia, farmers have practiced the cultural system for centuries and ensuring a stable yield. The farmer can maintain the fertility of the soil in a controlled manner. However, the equilibrium of fertility and yield production is disturbed due to the increase in production by the usage of seed varieties, chemical fertilizers, and pesticides (Priya and Ramesh, 2018). In recent years, the population is increased rapidly. Crop production was not able to fulfill the demand of the current population. The importance of nutrient-rich soil in the production of food, agriculture, and industry has been increasing. With the improvement of nutrient research, the correct ratio of nutrients has a critical role in increasing farming yield. In this work, we focus on optimizing the nutrients, i.e., Nitrogen (N), Phosphorous (P), and Potassium (K), together as N-P-K, by using the time-series data from the previous cultivation period. The improved genetic algorithm is proposed to optimize the yield production and recommend setting the nutrients values before the cultivation period. The research uses the recommendation of German scientist Justus von Liebig proposed the theory that states the value of N-P-K values are essential for crop improvement (Priya and Ramesh, 2018). Therefore, the proposed model recommended the optimized setting of nutrients for predicting the attainable yield. The method helps the farmer to manage the content of N-P-K values for every farmland in agriculture.

The problem of optimization terms as a combinatorial optimization problem. The natural evolutionary process inspires evolutionary computation (EC) (Hochba, 1997). EC has been applied to several combinations of task in data mining (Ahmed et al., 2021), scheduling problem and sequence planning (Xu et al., 2020). To explore the vast search space of optimization task, EC-based approaches, i.e., genetic algorithm (Lin et al., 2014) and ant colony optimization (Wu et al., 2017) are utilized in many domains and applications. However, the EC-based optimization typically searches for the global optima, i.e., moving towards the best fitness values; sometimes, EC methods miss the local optimization. The EC-based optimization methods are inefficiently able to search for the newly optimized parameters. We propose an improved GA method to recommend the optimized nutrients to address optimization, thus resulting in high yield production. Our approach offers a novel alternative to finding optimal nutrients to increase yield production while maintaining soil fertility. The major contributions are:

1. We have improved the population initialization strategy by using the time series soil nutrients. The proposed method helps to reduce search space and reduce the missing local optimization parameters.
2. We have introduced the neighborhood exploration method to speed the evolution process and increase the convergence rate. We introduce a repair method to reduce the invalid combination of the optimized parameters. Also, we introduce a reduction prevention method to maintain high optimize parameters.
3. Experimental results showed that an improved population initialization strategy significantly improved the nutrient recommendation and yield production performance compared to the traditional method.

The rest of the paper discusses as follows. First, in Section 2, we discuss the related work in the nutrient recommendation and increasing yield production to various farm situations. Section 3 discusses some preliminary information and problem statements. Section 4 discusses the proposed model and the framework. Section 5 describes the outcome of the proposed model and its comparison with the traditional approach through our thorough experimental analysis. Finally, the conclusion and possible future enhancements are discussed in Section 6.

2. Literature review

Nowdays, agriculture recommendation systems have emerged through various experiments using different approaches related to agriculture crops. The quality of seeds can be increased genetically, which results in high crop productivity. To improve the seeds genetically, the combination of the genotype and phenotype could be studied under the unique environment (Parent and Tardieu, 2014). The other factor that can increase productivity includes soil quality, weeds, nutrients level, and water management (Khoury et al., 2014). The learning-based mechanism also plays an essential role in improving the crop productivity and development of precision agriculture (Rehman et al., 2019). Khoshnevisan et al. addressed a greenhouse gas emission forecasting method is proposed to predict the potatoes yield in Iran farms (Khoshnevisan et al., 2014). They gathered the data for several crops in person; the developed model is tested under different conditions and tested by experts. The features that influence the forecasting output are electricity, fertilizers, and seed quality. The model can achieve 98% forecasting accuracy and 99% for gas emission. Muniasamy used the wireless sensor network for soil moisture detection and then helped in the automation of irrigation system (Muniasamy, 2020). The sensor collects information related to soil moisture and soil pH level to increase crop production. The developed system helps to give information related to moisture levels and soil requirements, fertilizers, and pesticides (Muniasamy, 2020). Bhar et al. (2020) introduced a coordinated descent algorithm for parameter calibration in agricultural model. A calibrated Root Zone Water Quality Model (RZWQM) model is also developed to determine the recommendations for fertilizer (Urea Ammonium Nitrate UAN) and irrigation amount which would help maximize the profit per hectare of the farm. Zou et al. (2020) presented an optimization model of drip irrigation and fertilization regimes for spring maize in Northwest China. Results then showed that the appropriate reduction of fertilization cannot significantly reduce the grain yield of spring maize, but low irrigation and fertilization amounts significantly reduced economic benefits. Xia et al. (2020) conducted a two-year field experiment in a typical rice–wheat cropping system in southern China to investigate the response of soil carbon input. Results then showed that the optimization of the nitrogen fertilization rate could increase food security, and soil organic carbon storage by enhancing soil carbon input, decreasing carbon output, and decrease nitrogen pollution caused by reactive nitrogen losses.

A machine learning-based for efficient crop yield recommendation is proposed (Suresh et al., 2021), which predicts the values for crops and gives a recommendation based on the predicted values (Suresh et al., 2021). In addition, Sharma et al. used to predict uncertain rainfall that affects the crops (Sharma et al., 2018). Furthermore, Khan and Ghosh used Meteorological Data of Chhattisgarh (CG) data to predict the crop yields (Khan and Ghosh, 2020). The data represents different crops nutrients levels (Khan and Ghosh, 2020). A neural network-based regression model is also proposed to predict the rain occurrence of the relevant geographical area. They collected the data from Ahmednagar, India, weather station. The features include temperature, humidity, values, and rainfall for the last ten years. The regression model can improve the selected geo-location rainfall prediction (Bendre et al., 2015). Different data mining algorithms have also been applied to agriculture datasets. For example, in (Hot and Popovic-Bugarin, 2015), Hot and Popovic-Bugarin introduced the clustering-based model incorporated with fuzzy *k*-mean. The soil is clustered based on the characteristic of the gathered sensor values. The paper is then compared the results with Google map and local streets' segmentation maps (Hot and Popovic-Bugarin, 2015), which stated that the developed model is suitable to present data to scientists and landowners. In (Navarro-Hellín et al., 2016), Navarro-Hellín et al. proposed two machine learning models respectively named Partial Least Square Regression (PLSR) (Navarro-Hellín et al., 2016) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (Navarro-Hellín et al., 2016) for managing irrigation in agriculture. The model could predict the water in the irrigation system that uses the soil condition, weather, and crop conditions as the major features for prediction.

3. Preliminaries and problem statement

Let $N = \{N_1, N_2, \ldots, N_m\}$ be a set of nutrients level, and the data be a set of instances such as $I = \{I_1, I_2, \ldots, I_n\}$ where each instance is a set of time-series data belonging to N and has a unique identifier called I_{id}. Each nutrient in an instance has a value (depending upon crop condition and sensor values) such as $v(N_k, I_c)$. Table 1 shows a simple example for the crop time-series database where nine years nutrient levels are used as features *(3×9 = 27)* marked as white colored column: *encoded chromosome with time series data*, yellow colored column: *recommended nutrient level for current year* as output variables, Grey colored column: *single objective high yield optimization* Furthermore, Table 2 shows the cotton crop data-set sample.

Problem Statement: This paper develops a model that enables efficient exploration of correct usage of nutrients for developing a knowledge-based system for the ICT environment. Develop knowledge is then applied directly to the environment, which recommends balancing soil fertility and crop production. The recommended setting also helps to improve crop yield. The model can optimize nutrient levels with no initial threshold values and extract patterns from the time-series data. The model takes advantage of the genetic algorithm to use the information and recommend optimizing remote environments.

Table 2
A sample of year wise data collection for the cotton farming.

SID	Time	Nitrogen	Phosphorous	Potassium
s1	2001	108	67	11
s2	2002	182	67	12
s3	2003	177	78	11
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
s10	2010	290	70	25

4. Designed model

We show the designed framework for ICT in Fig. 1, each sensor in the remote area has its set of nutrient levels (N_i). The sensor values are stored locally and sent to the database based on intervals (weekly, monthly, yearly) (Priya and Ramesh, 2018). All sensors for each nutrient are collected and merged through the Internet to log the extensive data set of the remote area. The designed algorithm is then applied and optimize for sequence nutrients for decision-making. We describe the detail of the framework below. The objective of the developed model is to maintain soil fertility (maintaining nutrient levels) and increase crop production (yield) simultaneously. The model extracts the optimization parameter by using the Euclidean distance-based search method. The proposed exploration and exploitation method helps to optimize locally main as well, globally. Sometimes, quality soil is not able to produce a high yield. The reason is the continuous cultivation of crops for a more extended time. As a result, the nutrients level drops after some years,

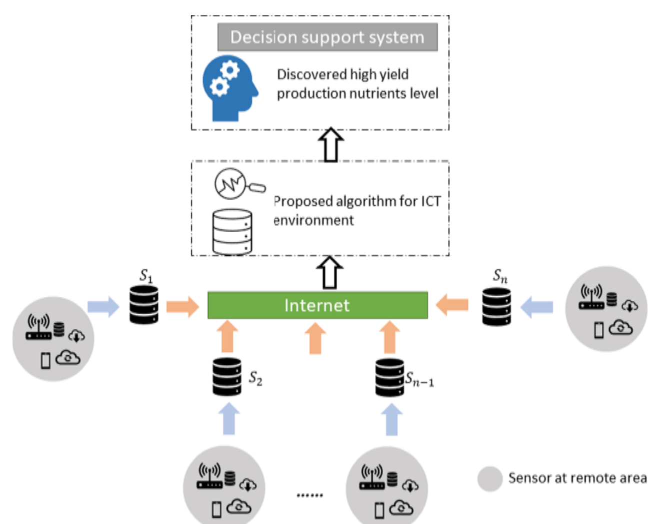

Fig. 1. A designed framework for ICT.

Table 1
A sample of initialized population.

Instance	*Nitrogen 2001*	*Phosphorous 2001*	*Potassium 2001*	*Nitrogen 2002*	*Phosphorous 2002*	*Potassium 2002*	. . . . .	*Nitrogen 2010*	*Phosphorous 2010*	*Potassium 2010*	*Yield*
I1	49	30	15	42	17	22	. . . . .	57	22	12	1717.5
I2	59	31	15	46	21	18	. . . . .	46	34	17	1878.9
I3	44	31	5	54	10	7	. . . . .	54	37	13	1880.2
I4	44	5	7	53	21	17	. . . . .	50	26	19	1719.5
I5	40	11	21	40	21	10	. . . . .	48	29	18	1961.6
I6	44	23	13	59	33	8	. . . . .	50	32	13	1720.1
I7	58	11	17	57	16	23	. . . . .	46	20	19	1880.5
I8	40	33	17	47	28	22	. . . . .	48	13	13	1720
I9	54	11	15	40	19	10	. . . . .	46	13	19	1878.3
I10	57	32	21	50	17	22	. . . . .	45	44	18	2039.1

resulting in quality and production.

For this reason, we used the series of data of the same cultivated area and then recommended the nutrient level before the crop. Compared to the traditional approach that only utilities the previous or current state of the soil, the developed model can recommend a set of nutrient levels and maximize the yield production. The used fitness function is shown in Eq. 1, where n is the number of the objectives, and $f_i(x)$ represents the i^{th} objective function for crop yields.

$$\text{Maximize} \quad F(x) = [f_1(x), f_2(x), \dots, f_n(x)] \tag{1}$$

Algorithm 1. Initialization

INPUT: Number of instances I, population pop size, number of generation Gen, Set of nutrients N, the size of neighbors n_s, crossover probability p_c, mutation probability p_m.
OUTPUT: Initialize individuals in a population.
1: $population \leftarrow 0$;
2: $i \leftarrow 1$;
3: **While** $i \leqslant Gen$ **do** ▹i represents number of generation
4: *chromosome*← Initialized for *len(N)* with 0;
5: *population*← select random number [1,*len*(I)];
6: $chromosome \leftarrow RouletteSelection(population)$;
7: $pop \leftarrow pop \cup chromosome$;
8: $pop \leftarrow IGA(pop, n_s, p_c, p_m)$;
9: $i++$;
10: **Return** *pop*.

4.1. Initialization

The initialization of the population is an essential step in the evolutionary algorithm. The population may cause a weak solution or very computational expenses (Ahmed et al., 2021). They applied the random initialization method to the database called a random selection. However, the issue with random selection is that it may cause invalid chromosomes and individuals, i.e., instances that are not in the database. In the first step, we propose the problem-specified initialization strategy. The value (nutrient values) encoded method is used. For the selection mechanism, we use the roulette selection mechanism. In Algorithm 1 (line 1–6), the chromosome is initialized with zero. Then random value is selected of length $len(N_i)$. The loop starts with roulette selection that select individual based on the roulette wheel where a population of all the chromosome (complete dataset) is placed. The roulette selection size is directly propositional to the fitness value of every chromosome; the larger the value, the greater the chance of the selection. In Algorithm 2 (line 1–4), we calculate the sum of the fitness value of each chromosome in the population. Then, we generated the random number to spin the roulette and get the index and chromosome values. For each chromosome, we assign the value for selection in the same manner. In this way, we complete the initialization method for the population size of *pop*. All the chromosomes of the individuals are populated and appended in the population matrix.

Algorithm 2. Roulette Selection

INPUT: *Population*.
OUTPUT: *indexindividual*.
1: $SumValue \leftarrow sum(N_i)$;
2: $CommulatedScore \leftarrow CMU(N_i)$; ▹Calculate the cumulative values
3: $Position_{roulette} \leftarrow sum(N_i) \times random$; ▹Spin wheel of the roulette
4: Search($CommulatedScore, Position_{roulette}$);
5: **Return** index individual.

Algorithm 3. IGA: population evolution

(*continued on next column*)

(*continued*)

INPUT: P, N_i, the size of neighbors n_s, crossover probability p_c, mutation probability p_m.
OUTPUT: Optimize population with higher yield values.
1: **for** *all* $i \in pop$ **do**
2: $individuals \leftarrow Eculidean_{distance}(P_i)$;
3: $P_i^{'} \leftarrow Neighbourhood(individuals, n_s)$;
4: $child \leftarrow CrossMutation(P_i^{'}, P_i)$;
5: $pop \leftarrow replace(P_i, child)$;
6: $Yieldindividual \leftarrow Max(Fitness, 2)$;
7: $Population \leftarrow replace(random(), 2, Yieldindividual)$;
8: **Return** $Optimize_{population}$.

4.1.1. Encoding

The encoding mechanism was depended on the domains and their applications. The commonly used encoding schemes are valued and binary as they result in the higher convergence and diversity of the solution (Ahmed et al., 2021). We use the value of the nutrient as the encoding method and time series of the last ten years. According to (Ahmed et al., 2021), the encoding mechanism depended on the two factors, i.e., order and values. The order helps in the permutation task, whereas the values and order are preserved by the binary and value encoded. Since we need to recommend nutrient values, so in this research, we are using the values encoding. The nutrient values (*N*, *P*, and *K*) are used as encoded values, as mentioned in the Eq. 2. The time series of the year-based encoding method are mentioned in Fig. 2.

$$B_{q,j} = \begin{cases} nutrient\_value(), & i_j \in I_q \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

4.1.2. Neighbor exploration and population evolution

The neighbor-based crossover and mutation method is proposed in the designed model. The Euclidean distance of the initialized population is calculated by using the equation, i.e., $d_{ij} = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2}$. The equation gives the distance between two individuals by calculating the root square and the difference between each point (Algorithm 3, line 2). The most similar individual is selected, thus exploring the global optimization. We select the individual neighbour's and then apply one point cross mutation operation, as mentioned in Algorithm 3 (Algorithm 3, line 3) and shown in Figs. 3 and 4.

For each iteration, we develop a strategy to transfer the data from one generation to another, as mentioned in Figs. 5 and 6. Two consecutive individuals are selected from the previous generation randomly. We replace it with the current generation, and the random replacement helps as better individuals improved to do the evolution in different directions (Algorithm 3, lines 6–7). Also, the search space of the population expanded with the inclusion helps in the population diversity and preventing the failure of local optimization.

As shown in Fig. 6, we also propose the population exploitation method that helps to lose the best individual. First, we merge the previous population and the new population. Then, we remove the duplicates individually. After that, we perform a ranking-based selection. Finally, the individual is sorted and selected based on the fitness values according to decreasing order.

5. Experimental evaluation

In this section, we used the dataset from the source (Priya and Ramesh, 2018). The amount of nutrients by the crop and applied to the past ten years has been discussed. Table 3 shows the characteristics of different crops. The best and maximum values are mentioned. The experiments are carried on Linux mint distro, core i7 processor, and 16 GB RAM. For an improved GA-based model, we set the population size to 100. The maximal generation is set to 100, the neighbourhood

$$\text{Maximize} \quad F(x) = [f_1(x), f_2(x), \ldots, f_n(x)] \tag{1}$$

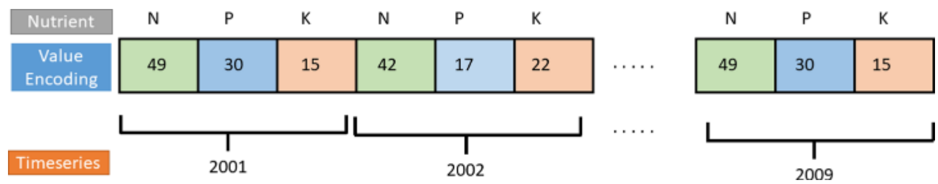

Fig. 2. Encoding example with time-series data.

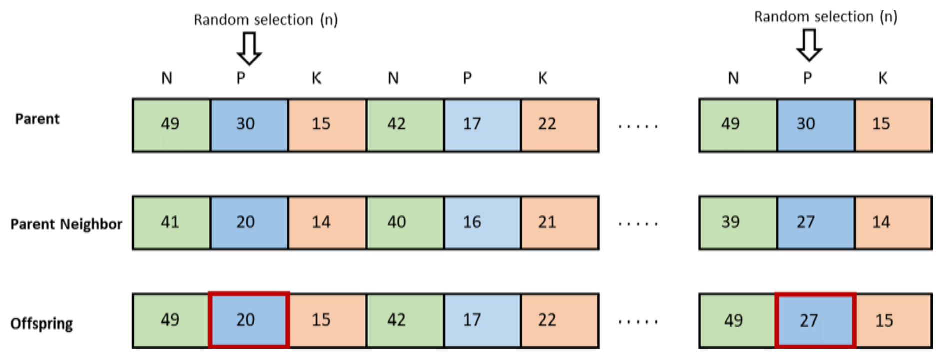

Fig. 3. Population offspring methodology.

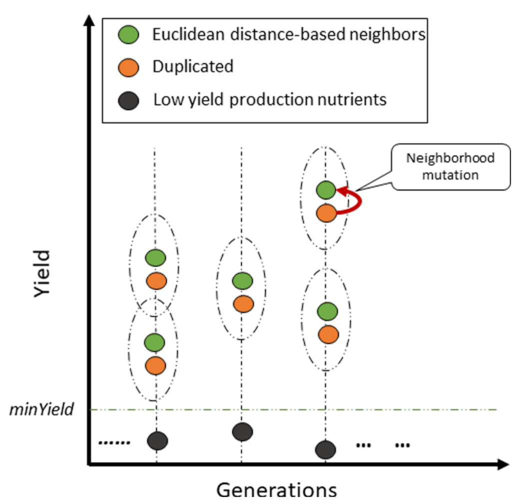

Fig. 4. Population exploration methodology.

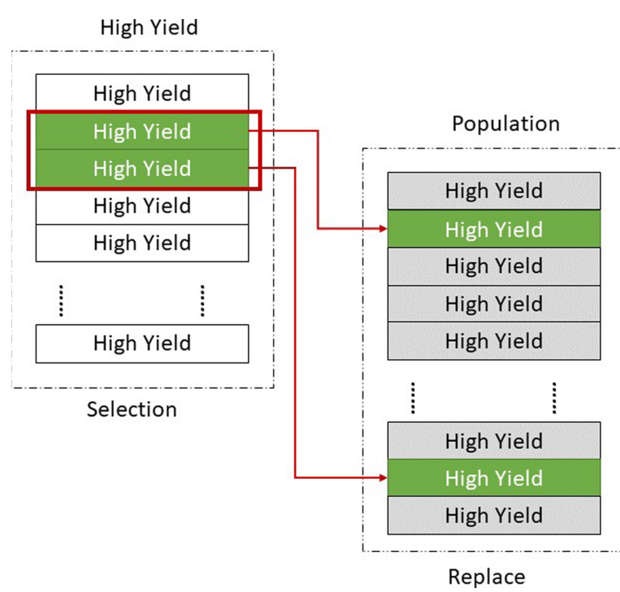

Fig. 5. Population selection mechanism.

exploration is set to 10, and mutation and crossover probability were set to 0.01 and 1.0, respectively. We then used the datasets from 2001 to 2009 and suggested the 2010 nutrient level for cotton, groundnut, maize, and rice.

Fig. 7 and Table 4 below depict all crop categories, which are used to analyze trends of nutrient loss. Each plot describes the level of the crop nutrient levels. As seen in the figure, the nitrogen level is almost double compared to the actual required by the plants for the cotton plant. The traditional settings lead to a low fertility level and result in low crop production. Based on the designed model, the recommended setting results in a higher yield. The phosphorous and potassium level applied with IGA is almost similar to the traditional one. However, in combination with the other nutrient, the nitrogen level helps to increase the yield production. For groundnut crops, nitrogen and phosphorous values are higher than compared to the traditional method. However, the value of potassium is lower. Thus, the resultant yield value is almost similar to the traditional. The model performs slightly better. For the maize crop, the model required more generation to expand more knowledge. For the maize crop, all the nutrient levels recommended by IGA are higher than the traditional method. As a result, the model can produce the $2,035$ quantity (kg/Hg) compared to the traditional approach with $1,865.47$ quantity (kg/Hg). For rice crops, both traditional and IGA methods have an equal suggestions. They are resulting in an equal performance of the yield production. Thus, the proposed model can perform better for cotton and groundnuts, whereas maize and rice production is equally. For that reason, maize and rice are required to be run for more generations.

After experimentation, the proposed method is found to perform better and produce a higher number of yields. It is found that a better nutrient amount can be achieved by using the proposed model. If the right amount of nutrients is applied to crops, then a high yield can be

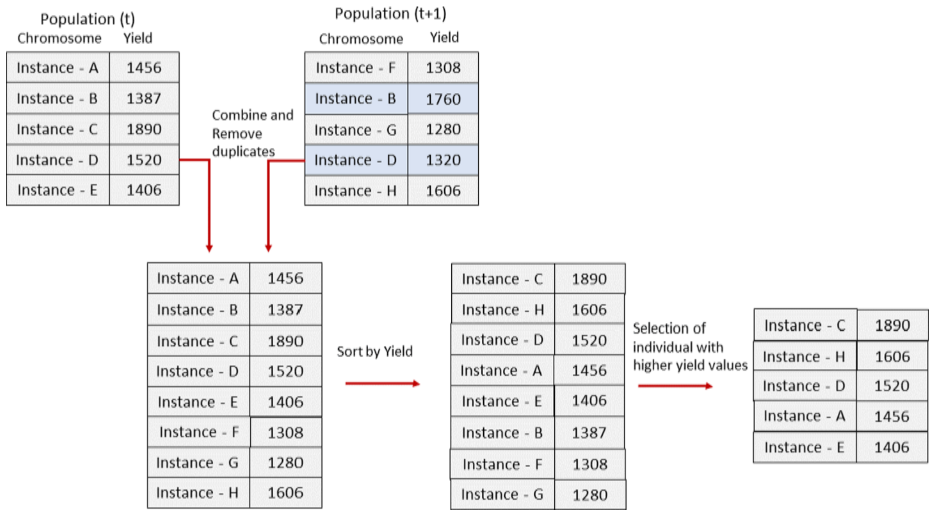

Fig. 6. Population exploitation method.

Table 3
Characteristic of dataset used.

Type	Nutrients	Max	Min	Best max	Best min	Yield	Best Yield
Cotton	*Nitrogen*	350	180	290	110	1600	1900
	Phosphorous	110	60	70	60		
	Potassium	30	15	25	10		
Ground nut	*Nitrogen*	90	40	30	15	1100	1600
	Phosphorous	110	60	55	35		
	Potassium	35	15	45	25		
Maize	*Nitrogen*	275	90	170	60	1400	2400
	Phosphorous	70	30	50	15		
	Potassium	90	20	60	10		
Rice	*Nitrogen*	80	70	55	45	110	2200
	Phosphorous	38	20	35	15		
	Potassium	25	10	20	10		

achieved. Using the proposed model, crop yield production increased and gave super ability to decide the right combination of different types of available resources. This will helps farmers and agriculture experts to adopt the method for other crops. The automation of the N-P-K helps to avoid manual estimations. The method also improved if a high volume dataset of different crops can be accessible and targets yield values properly indexed with soil type and location.

6. Conclusion and future work

This paper proposed an improved genetic algorithm (IGA) to recommend an optimal setting for nutrients to different crops. The algorithm adopts an optimization scheme, which involves a neighborhood exploration and exploitation strategy. The model was able to improve local optimization to prevent the local premature individual in the population strategy. We also use diversity to maintain a method to expand population knowledge. The results in the real-world datasets showed that the proposed IGA method could perform better against the standard recommendation. Thus, the algorithm can optimize the yield

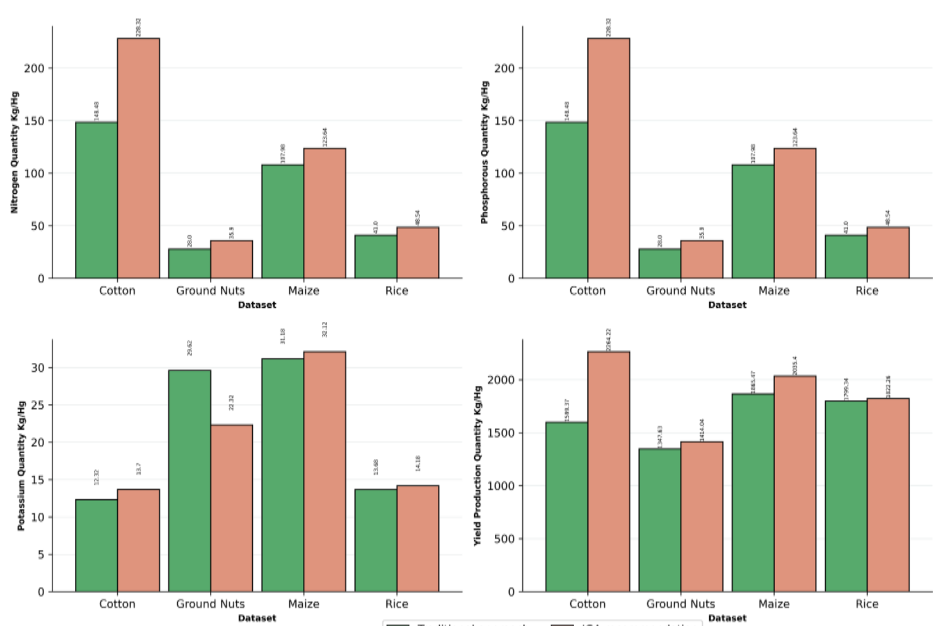

Fig. 7. Results comparison with the traditional method for Nitrogen, Phosphorous, Potassium and Yield.

Table 4
The data-set comparison in terms of best, worst, average and standard deviation.

Dataset	Method	Worst	Best	Average	Std.
Cotton	*Traditional [6]*	1597.60	1601.20	1599.37	0.86
	IGA	**1960.40**	**2320.20**	**2264.22**	**97.89**
Ground nuts	*Traditional [6]*	1149.60	1500.80	1347.63	88.27
	IGA	**1249.90**	**1450.90**	**1414.04**	**61.65**
Maiz	*Traditional [6]*	1498.20	2299.30	1865.47	168.44
	IGA	**1699.40**	**2099.20**	**2035.40**	**130.28**
Rice	*Traditional [6]*	1559.00	2120.00	1799.34	132.26
	IGA	**1640.90**	**1961.00**	**1822.26**	**91.37**

and maintain nutrient levels. In the future, we plan to optimize the search strategy and individual repair methods to extract valuable parameters. This will help to reduce the computation resources and improve the recommendation to maintain crops for soil fertilization. Furthermore, the AI/ML models or multi-objective optimization models can also be considered to solve the limitation of the optimization issue if there is a suitable model to tune the parameters for further implementation efficiently.

Declaration of Competing Interest

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

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References

Ahmed, U., Lin, J.C.W., Srivastava, G., Yasin, R., Djenouri, Y., 2021. An evolutionary model to mine high expected utility patterns from uncertain databases. IEEE Trans. Emerg. Top. Comput. Intell. 19 (1), 19–28.
Bendre, M.R., Thool, R.C., Thool, V.R., 2015. Big data in precision agriculture: Weather forecasting for future farming. In: The International Conference on Next Generation Computing Technologies, pp. 744–750.
Bhar, A., Kumar, R., Qi, Z., Malone, R., 2020. Coordinate descent based agricultural model calibration and optimized input management. Comput. Electron. Agric. 172, 105353.
Casta neda-Miranda, A., Casta no-Meneses, V.M., 2020. Internet of things for smart farming and frost intelligent control in greenhouses. Comput. Electron. Agric. 176, 105614.
Hochba, D.S., 1997. Approximation algorithms for np-hard problems. ACM SIGACT News 28 (2), 40–52.
Hot, E., Popovic-Bugarin, V., 2015. Soil data clustering by using k-means and fuzzy k-means algorithm. In: The Telecommunications Forum Telfor, pp. 890–893.
Khan, H., Ghosh, S., 2020. Crop yield prediction from meteorological data using efficient machine learning model. In: Proceedings of International Conference on Wireless Communication, pp. 565–574.
Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H., Rajaeifar, M.A., 2014. Application of artificial neural networks for prediction of output energy and GHG emissions in potato production in Iran. Agric. Syst. 123, 120–127.
Khoury, C.K., Bjorkman, A.D., Dempewolf, H., Ramirez-Villegas, J., Guarino, L., Jarvis, A., Rieseberg, L.H., Struik, P.C., 2014. Increasing homogeneity in global food supplies and the implications for food security. Proc. Nat. Acad. Sci. 111 (11), 4001–4006.
Klerkx, L., Jakku, E., Labarthe, P., 2019. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. Wageningen J. Life Sci. 90–91, 100315.
Lin, C.W., Zhang, B., Yang, K.T., Hong, T.P.H., 2014. Efficiently hiding sensitive itemsets with transaction deletion based on genetic algorithms. Scientific World J. 5, 398269.
Lin, J.C.W., Srivastava, G., Zhang, Y., Djenouri, Y., Aloqaily, M., 2021. Privacy-preserving multiobjective sanitization model in 6g iot environments. IEEE Internet Things J. 8 (7), 5340–5349.
Muniasamy, A., 2020. Applications of data mining techniques in smart farming for sustainable agriculture. In: Modern Techniques for Agricultural Disease Management and Crop Yield Prediction, IGI Global, pp. 142–178.
Navarro-Hellín, H., del Rincon, J.M., Domingo-Miguel, R., Soto-Valles, F., Torres-Sánchez, R., 2016. A decision support system for managing irrigation in agriculture. Comput. Electron. Agric. 124, 121–131.
Parent, B., Tardieu, F., 2014. Can current crop models be used in the phenotyping era for predicting the genetic variability of yield of plants subjected to drought or high temperature? J. Exp. Bot. 65 (21), 6179–6189.
Priya, R., Ramesh, D., 2018. Adaboost.RT based soil n-p-k prediction model for soil and crop specific data: a predictive modelling approach. In: Big Data Analytics. Springer, pp. 322–331.
Rehman, T.U., Mahmud, M.S., Chang, Y.K., Jin, J., Shin, J., 2019. Current and future applications of statistical machine learning algorithms for agricultural machine vision systems. Comput. Electron. Agric. 156, 585–605.
Sharma, A.K., Chaurasia, S., Srivastava, D.K., 2018. Supervised rainfall learning model using machine learning algorithms. In: International Conference on Advanced Machine Learning Technologies and Applications, pp. 275–283.
Suchithra, M.S., Pai, M.L., 2020. Improving the prediction accuracy of soil nutrient classification by optimizing extreme learning machine parameters. Informat. Process. Agric. 7 (1), 72–82.
Suresh, G., Kumar, A.S., Lekashri, S., Manikandan, R., 2021. Efficient crop yield recommendation system using machine learning for digital farming. Int. J. Modern Agric. 10 (1), 906–914.
Wu, J.M.T., Zhan, J., Lin, J.C.W., 2017. An ACO-based approach to mine high-utility itemsets. Knowl.-Based Syst. 116, 102–113.
Xia, L., Shu, K., Wang, S., Zhou, W., Chen, D., Yan, X., 2020. Optimizing nitrogen fertilization rate to enhance soil carbon storage and decrease nitrogen pollution in paddy ecosystems with simultaneous straw incorporation. Agric. Ecosyst. Environ. 298, 105986.
Xu, W., Tang, Q., Liu, J., Liu, Z., Zhou, Z., Pham, D.T., 2020. Disassembly sequence planning using discrete bees algorithm for human-robot collaboration in remanufacturing. Robotics Comput.-Integrated Manuf. 62, 101860.
Zamora-Izquierdo, M.A., Santa, J., Martínez, J.A., Martínez, V., Skarmeta, A.F., 2019. Smart farming IoT platform based on edge and cloud computing. Biosyst. Eng. 177, 4–17.
Zou, H., Fan, J., Zhang, F., Xiang, Y., Wu, L., Yan, S., 2020. Optimization of drip irrigation and fertilization regimes for high grain yield, crop water productivity and economic benefits of spring maize in northwest china. Agric. Water Manag. 230, 105986.