Deep intelligence for sustainable farming: a swarm-empowered data analytics architecture

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ABSTRACT

The inclusion of complex patterns of data in precision agriculture (PA) induces a greater degree of challenges from the perspective of carrying out conventional analytical operations. Although proliferated use of artificial intelligence (AI) has been noticed to yield some promising results to address such issues, yet they too have many shortcomings. Hence, the current manuscript introduces an innovative hybrid AI scheme towards enhancing the analytical operations necessary for decision-making in smart farming. The proposed scheme hybridizes a deep neural network (DNN) with a novel swarm intelligence (SI) model for optimizing the performance of its adopted deep learning (DL) model. Tested on a standard dataset of agriculture, the proposed model exhibited a 10% increase in accuracy and 40% faster response time when compared with conventional machine learning (ML) models, DL models, and SI models. The study contributes to a novel benchmark towards time-efficient, scalable, and intelligent analytics on PA.

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1. INTRODUCTION

Precision agriculture (PA) represents a modernized approach towards farming management where the agricultural inputs are optimized using data-driven technologies [1]. The idea of PA is to increase sustainability, efficiency, and productivity. Real-time data is collected from environmental, weather, soil, and crop factors, and used to make informed decisions. Various key technologies used in PA are automated machinery and robotics, variable rate technology (VRT), drones and satellites, and location-based information systems. There are various applications for PA, ranging from weed control, livestock management, crop yield monitoring and forecasting, pest control, irrigation management, crop monitoring, to soil and land mapping. Most recently, there have been various reported studies stating higher involvement of artificial intelligence (AI) in PA. There are a number of specific problems or challenges associated with PA, which can only be optimally resolved by adopting an AI-based approach, namely data overload and complexity, as well as spatial and temporal variability, demands of predictive-decision-making, uncertainty in biological systems, demands of real-time decision-making, identification of diseases and pests, and optimization of inputs [2]. Hence, AI has evolved in PA from i) computer vision towards disease diagnosis, weed detection, and crop monitoring; ii) clustering and classification towards categorization of soil type and field zoning; iii) time-series forecasting contributing towards yield and weather prediction. AI exists in various forms, and yet machine learning (ML) and deep learning (DL) are the only AI variants that are found dominant in the research domain. On the contrary, swarm intelligence (SI) is a much less spoken about approach, although it is an integral part of AI models. The effectiveness of ML and DL has been much reported in many studies; while it is interesting to note that SI models are equally powerful. Adoption of SI can assist in PA via coordination with autonomous drone/robot swarms. It can also be used for making a decision towards the usage of water and fertilizer, where the foraging behavior of ants can be used for minimizing cost. SI models can also be used for identifying and responding to outbreaks of pests where agents use swarm dynamics to frame up pest behavior in order to forecast spread patterns of disease or something specific related to a plant's health. Apart from this, it is noted that hybrid models too are claimed for optimized performance in PA; however, such hybridizations are seen mainly with ML and DL models and not with SI models [3]. Prior to that, it is necessary to understand the related work associated with PA, considering varied cases of agricultural problems to realize the contribution of existing state-of-the-art AI models towards improving PA-based operations.

Different types of literature have been reviewed to understand the implications of different variants of AI models towards PA. A recent study using random forest (RF) methods exhibits a potential strength towards solving classification problems in PA quite efficiently, while it can also handle regression [4], [5]. However, RF models have dependencies of trees, which could increase the computational effort, while their interpretation is quite complex in contrast to a single decision tree. Various researchers have also used support vector machine (SVM) towards addressing classification problems in PA on varied forms of data for pest detection, weed identification, and crop health [6]–[9]. Although they have a very good generalization performance and are quite effective in high-dimensional spaces, SVM-based methods are unsuitable for large-scale datasets. Apart from ML models, there is an increasing usage of DL models too. Recent studies using deep neural network (DNN) have been found to assist in predictive modelling as well as towards solving non-linear relationship-based complications in PA [10]–[12]. Irrespective of its extensive capabilities towards learning complex patterns, such method has increased energy and computational cost. Another widely adopted DL model is convolutional neural network (CNN), witnessed in existing system which mainly process image-based tasks towards mapping crop type, classification of weeds, and detection of diseases. The majority of CNN-based approaches have reported unbeatable classification accuracy performance, and yet they are actually not suitable for non-visual data, which is one of their downsides [13]–[16]. It also involves computationally expensive training operations. There are various studies where SI has been used towards smart farming. Some of the studies have reportedly used ant colony optimization (ACO) towards optimal resource allocation (pesticides/fertilizer routes) as well as for planning field path (for autonomous tractors) [17]–[20]. Although ACO approaches are efficient for solving discrete combinatorial problems yet they are characterized by slow convergence speed. Another frequently used SI model is particle swarm optimization (PSO), which is reportedly used for hyperparameter tuning of ML models as well as optimizing yield function, planting strategies, and irrigation schedules [21]–[25]. PSO-based approaches are quite simplified to be implemented, and yet they have sub-optimal performance on high-dimensional PA data. The existing system has also reportedly used genetic algorithm (GA) towards the feature selection process as well as for various process management in smart farming [26]–[28]. GA-based approaches have effective global optimization performance, and yet they are a computationally expensive process.

The identified research problems are as follows: i) there are higher dependencies of high-quality dataset for AI models in PA which is quite impractical all the time, ii) frequent adoption of AI models in PA also means their nature to be of blackbox form which reduces reliability and trust for farmers to use them, iii) there is sub-optimal scaling of optimization models of an AI, especially when subjected to diverse and large farming area in real-time, and iv) it is also challenging task to integrate multiple AI techniques in PA where various uncontrollable environmental factors existing in real scenario. Hence, the proposed system addresses these problems modular approach, which involves enriching data quality, simplified and effective feature selection methods, and a hybridization of DL and SI methods as a novel AI technique.

The aim of the proposed study is towards introducing a hybrid AI model integrating a DL model and an SI model towards enhancing the analytical operations involved in generalized PA applications, e.g., decision-making, classification, and processing. The contributions of the model are as follows: i) the model carry out selection of potential relevant attributes using simplified and yet efficient tree-based feature selection, ii) the study presents an abstractive modelling approach by hybridizing DL and SI for innovative analytical structure, iii) the hybrid model uses DNN for processing PA data while its hyperparameters are revised using a novel metaheuristic titled enhanced learning and optimization swarm (ELOS), which is based on SI approach, and iv) an extensive study carried out to prove effectiveness of proposed model benchmarked with standard dataset when compared with frequently adopted AI models. The structure of the manuscript is as follows: section 2 presents an elaborated discussion of the adopted research method, while result is discussed in section 3, and the conclusion is given in section 4.

2. METHOD

The proposed study adopts a novel mathematical and analytical framework with a sole target towards improving the analytical operation associated with large-scale agricultural data using a hybrid AI system. The scheme integrates DNN methodology with an innovative ELOS for developing a novel. Figure 1 highlights the architectural design adopted in the proposed study, constructed with various components with an explicit set of operations performed by them. The model takes the input of raw data from an agricultural context, which is then subjected to preprocessing, while the selection of potential features is carried out using a tree. Further, a hybrid form of an AI model using DNN and novel ELOS is implemented to undertake optimal decision-making in PA.

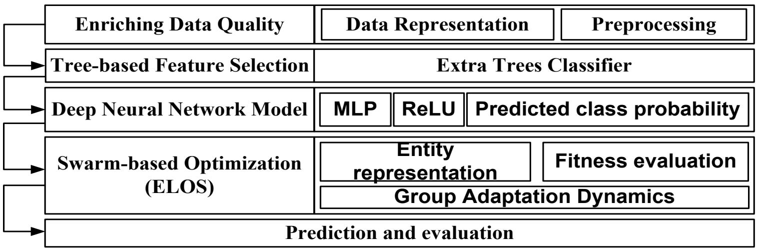

Figure 1. Architecture of proposed hybrid AI model

2.1. Enriching data quality

This is the first implementation module that ensures cleaner and consistent collection of raw input data from diverse agricultural monitoring devices. The system carries out a preprocessing operation that consists of handling missing values, followed by normalizing the scales of features. Further encoding is carried out for categorical variables. Consider an empirical representation of the raw agricultural dataset as $D = \{(x_i, y_i)|i = 1, 2, \ldots, N\}$, where the variable xi represents $[x_{i1}, x_{i2}, \ldots, x_{id}]$ are all real-number-based data depicting a feature vector. It can also be considered as sensory readings (e.g., humidity, temperature, and soil pH). The second variable y_i is a binary class label [0, 1] depicting the possible outcomes, while d and N represent the number of original features and the cumulative number of instances. The feature is then processed through normalization as (1).

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{1}$$

In (1), the variable μ_j and σ_j represent the statistical mean and standard deviation, respectively, associated with the j^{th} feature $(j \in (1, 2, \ldots, d)$. Adoption of normalization contributes towards equal emphasis and participation of all variables during the model training. This model generates an outcome of a highly structured dataset from noise. Unlike conventional preprocessing operations that consider all features in the same manner, the proposed module is specifically optimized for PA data, which operates consistently towards the process of feature selection.

2.2. Tree-based feature selection

This module is responsible for retaining the most potential information while also assisting in minimizing the dimensionality of PA data. The proposed scheme uses an extra tree classifier for applying a ranking strategy for features in order to improve model accuracy and optimize the computational efficiency. An extra tree classifier is a type of ensembled structure formed with an arbitrary decision tree. The significance value I_j towards all the individual feature j is mathematically evaluated as (2).

$$I_j = \sum_{t=1}^{T} \sum_{n \in} \triangle\, i(n). I_{feature\,(n)-j} \tag{2}$$

In (2), it can be noted that formulation of significance value I_j is dependent upon the number of trees T, the set of nodes associated with tree t as N_t, the impurity reduction at the nth node as $\Delta i(n)$, and the indicator function I. The prime motive of this operation is to assess the impact of each feature towards reducing the uncertainty during decision-making over various trees. The system further selects the k^{th} top features that are mathematically represented as (3).

$$F_{selected} = Top_k(\{I1, I2, \dots, Id\}) \quad (3)$$

In (3) highlights the selected top features based on their significance score. The selected features are ranked, which is statistically significant towards the task of prediction. In contrast to the conventional method of feature selection using correlation analysis or univariate filtering, the proposed module can acquire a sophisticated set of information pertaining to complex nonlinear interactions among the involved variables. The novelty of this module resides in its capability towards combining trees with structural randomness for efficiently managing the heterogeneous and high-dimensional PA data. The idea is to improve both computational efficiency and model performance.

2.3. Deep neural network model

The key goal of this module is towards performing optimized learning operations with extensive abstraction from the chosen features, followed by precise prediction. This module consists of a different number of hidden layers towards transforming the input PA data into progressively sophisticated forms of representation. Consider a reduced feature matrix $X` \in R^{Nxk}$ where the value of $k$ is much less than $d$. The system then formulates the multi-layer perceptron where the input layer is depicted as $h(0) = X`$, hidden layers are depicted as for $l = 1$ to L, $h^{(l)} = \sigma(W^{(l)}.h^{(l-1)} + b^{(l)})$, and the output layer is depicted as $\hat{y}_i = sigmoid(w^{(o)}.h^{(L)} + b^{(o)})$. In all these simplified forms of expression, the variables $W^{(l)}$ and $b^{(l)}$ represent weights and biases, respectively, for the lth layer, while the variable $\sigma(.)$ represents an activation function. The system also uses the sigmoid function $sigmoid(z) = 1/(q + e^{-z})$ is meant for mapping with the binary outcome of (0, 1) and $\hat{y}_i$. It is considered as forecasted probability of a class. Further, the binary cross-entropy loss is minimized in order to train the DNN model, which is mathematically expressed as (4).

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i.\log(\hat{y}_i) + (1 - y_i).\log(1 - \hat{y}_i)] \quad (4)$$

According to (1), it can be noted that an intricate relationship among features is captured by the model, where non-linearity is introduced by the activation function from each layer, while propagation of information is carried out via weighted connections through the network. This model generates an outcome of a trained model towards classifying and forecasting the results contextually with PA applications. Conventional ML models encounter challenging situations towards analyzing nonlinear patterns in massive and complex forms of PA datasets; however, the DNN model provides the capacity for DL and enhanced accuracy that further contributes to dynamic adaptability. The proposed architecture is highly dynamic, while the swarm-based intelligence scheme of ELOS is used for fine-tuning its operation for performance-driven and data-efficient modelling.

2.4. Swarm-based optimization (ELOS)

The prime goal of ELOS is towards optimizing the learning configuration and architectural parameters of the prior DNN model for reducing the response time and increasing the accuracy. The formulation of this module is carried out based on ecological swarms exhibiting their opportunistic and adaptive behavior. The formulation of the innovative ELOS module is designed considering the cognitive behavior of predator swarms with an opportunistic dynamic of the group. The individual nodes fine-tune their behavior based on the dynamics of local groups. Different from conventional approaches of SI, ELOS deploys a learning strategy of local subgroups considering adaptive characteristics. The proposed scheme considers the representation of entities using diverse parameters. This module introduces a learning strategy where the exploration of the solution space in different regions is carried out by a software agent. The system considers a software agent $a_i \in R^p$ depicts the solution vector that is responsible for encoding the learning rate, activation function, neurons per layer, and number of hidden layers. An empirical statement of fitness evaluation $f(a_i)$ is represented as (5).

$$f(a_i) = \alpha.Accuracy\ (a_i) - \beta.ResponseTime(a_i) \quad (5)$$

In (5), the variables α and β represent the scaling coefficient. The system further presents a dynamics of group adaptation where the position is updated by an agent on the basis of an opportunistic factor γ and a_j^* representing a local best, where a subgroup G consists of all the agents a. The expression of group adaptation of an agent is as (6).

$$a_i^{(t+1)} = a_i^{(t)} + \delta \quad (6)$$

In (6), the variable δ represents $\gamma.\left(a_j^* - a_i^{(t)}\right) + \epsilon$ and the attribute $\gamma[\in (0,1)]$ is used for controlling rate of convergence. The parameter $\in$ is nearly similar to the Gaussian noise term $N(0, \sigma^2)$ that is adopted for maintaining the diversity. All the software agent that are found to sub-optimally perform is subjected to re-initialization to a novel arbitrary position after every R iteration, where R represents the reset rule. This module generates an outcome of an optimized DNN model where various hyperparameters are autonomously selected. Different from existing SI approaches, this module combines strategic reset with local learning for resisting any form of premature convergence. The novelty of this module is that it yields robustness within the PA dataset with enhanced accuracy of prediction and faster convergence.

3. RESULT AND DISCUSSION

The logic of the proposed system is written in Python, considering a normal Windows 64-bit environment. Using Jupyter notebook, the design process is accomplished using various libraries and packages, viz. NumPy, Pandas, Matplotlib, Seaborn, TensorFlow/Keras, and Scikit-learn. The environment has been simulated on an Intel Core i7 processor with 16 GB of DDR4 RAM. The proposed system execution is carried out on the CPU and doesn't require any explicit GPU within the session time. Using the standard dataset [29] and a similar test environment, the proposed model (Prop) that consists of ELOS optimizer, DNN, and tree-based feature selection is compared with i) two potential ML models, viz. RF, and SVM, ii) two potential DL models, viz., baselined DNN and CNN, and iii) two potential SI models, i.e., PSO-tuned DNN and GA tuned DNN. The complete assessment and benchmarking are carried out considering accuracy, precision, recall, F1-score, and response time.

3.1. Accomplished outcome

The outcome is shown in Table 1, which exhibits the Prop to accomplish maximum accuracy of classification (acc =93%) while it records minimized duration of response time (r_{time} =0.78 s) in contrast to all existing models. The primary reason for efficiency and model precision is due to the combination of ELOS SI and adopted feature selection using a tree. It can also be noted that the proposed system retains a higher F1-score (val =0.91) to exhibit its balanced specificity and sensitivity over agricultural classes. Overall, the outcome of the proposed study represents its real-time capability, accuracy, and scalability.

Table 1. Numerical outcomes of the study

Model	Accuracy	Precision	Recall	F1-score	Response time (sec)
RF	0.84	0.82	0.80	0.81	0.89
SVM	0.81	0.78	0.76	0.77	1.14
Baseline DNN	0.87	0.85	0.83	0.84	1.22
CNN	0.88	0.86	0.84	0.85	1.38
PSO+DNN	0.89	0.87	0.86	0.86	0.97
GA+DNN	0.88	0.86	0.84	0.85	1.01
Prop (ELOS+DNN)	0.93	0.92	0.91	0.91	0.78

3.2. Discussion

The accomplished outcome of the study exhibited in Figure 2 shows that proposed system offers approximately 10.2% better accuracy in contrast to conventional ML model (RF and SVM), approximately 6.8% increased accuracy in contrast to traditional DL models (baseline DNN and CNN), and approximately 8.4% of maximized classification accuracy in contrast to conventional SI models (PSO+DNN and GA+DNN). This can be realized from Figure 2(a). Similarly proposed scheme contributes to 12.5%, 7.6%, and 9.1% better precision in contrast to conventional ML, DL, and SI models, as shown in Figure 2(b), which also shows recall performance of nearly similar trends. The F1-score of the proposed system is witnessed to offer 11.9%, 7.2%, and 8.9% enhanced performance in contrast to traditional ML, DL, and SI models, respectively (Figure 2(c)). Similarly, Figure 2(d) shows the proposed scheme to exhibit 34.5%, 42.3%, and 27.1% faster response time in contrast to ML, DL, and SI models.

The prime reason for the underperformance of conventional models can be attributed to the fact that ML models do not offer abstraction layers, while they have issues pertaining to bias/overfitting on voluminous data. In the conventional DL model, the baseline DL models don't include optimization that results in plateauing or restricted convergence, mainly due to non-optimal hyperparameters. On the other hand, the conventional SI models are found to get engaged to local optima that don't possess adaptive characteristics towards balancing exploitation and exploration. On the contrary, the proposed scheme integrates a DL model optimized by a novel SI model of ELOS, and tree-based feature selection is performed towards stabilized classification and enhances generalization. Apart from this, it is noted that there is an exhaustive usage of rule-based structure in conventional ML models that results in a longer duration of evaluation. Further, the computation in the DL model is associated with complex layers lacking optimization, resulting in increased response time. Inclusion of iterations within SI models is another reason for its maximized response time.

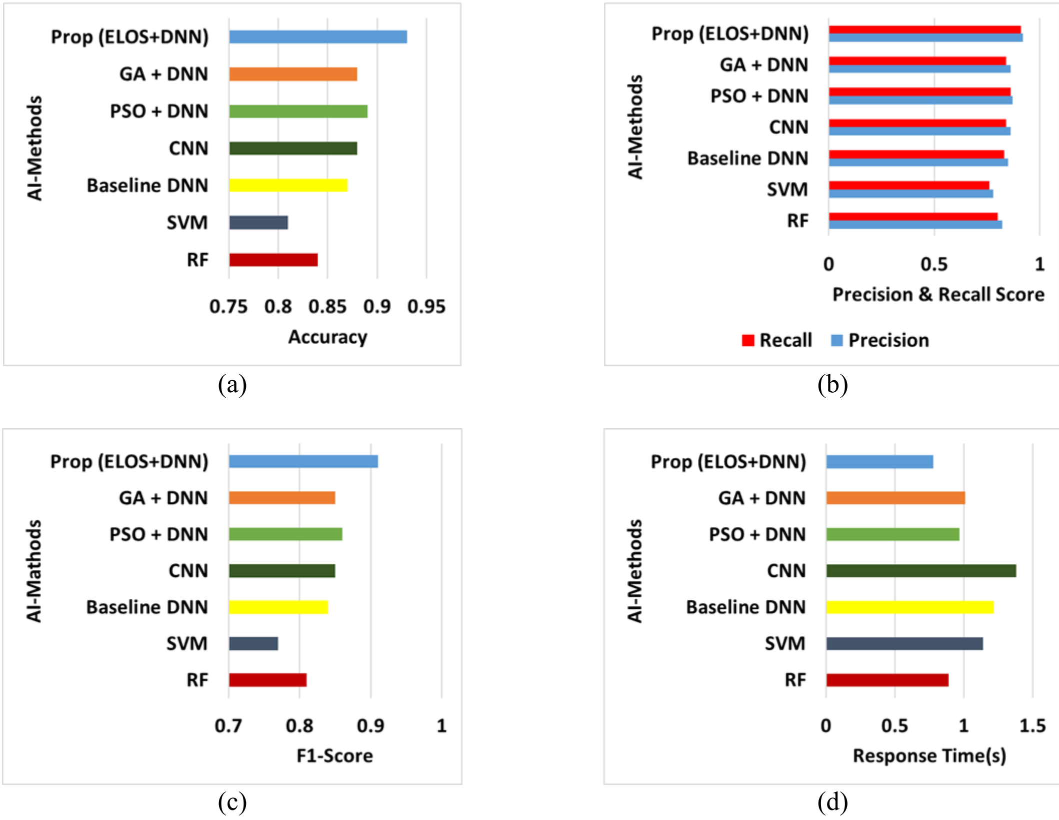

Figure 2. Benchmarked outcomes of the study of (a) accuracy, (b) precision and recall, (c) F1-score, and (d) response time

4. CONCLUSION

The proposed study presents a novel analytical and computational framework that is capable of optimizing the decision-making in PA by integrating a novel SI model with a DL model. The key contribution is toward improving the analytical operation when exposed to a voluminous PA dataset. It is noted that preprocessing overhead can be potentially controlled by minimizing irrelevant features, which is taken care of by adopting tree-based selection of attributes. Further, ELOS is used for fine-tuning the DNN model that results in an optimized training model. The learning outcome contributed by the study shows that computational efficiency is contributed by the proposed tree-based attribute selection, while high-quality flow of information is contributed by the abstractive data model, and optimization of intelligent hyperparameters is carried out by ELOS. Overall, the proposed study showcases that the deployment of AI systems toward real-time decision-making is quite feasible in PA for undertaking real-time decision-making from the perspective of smart irrigation control, yield prediction, and monitoring of crop health. On the grounds of accomplished results, it can be stated that the proposed scheme maintains a good balance between increased classification accuracy and faster response time, which makes it more applicable in futuristic real-time applications and services in PA. The future work will involve further optimizing the entire process by adopting more advanced versions of DL models with equal emphasis on low computational cost and resource inclusion.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [KMP], upon reasonable request.

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