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RESEARCH ARTICLE

Neuro-EvoSwarm Optimizer (NESO): A Hybrid Deep Learning, Genetic Algorithm and Particle Swarm Optimization Framework for Seasonal Multicropping Strategy Optimization under Drip Irrigation

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ABSTRACT

Seasonal multi cropping under drip irrigation requires simultaneous consideration of crop productivity, economic return, soil characteristics, climatic variability, fertilizer management and irrigation water use. This paper presents the Neuro-EvoSwarm Optimizer (NESO), a hybrid decision-support framework that integrates Deep Learning (DL), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The framework first preprocesses agricultural data by handling missing or inconsistent records, encoding categorical variables, scaling numerical features and selecting relevant attributes. A Deep Learning prediction module estimates crop yield and economic profit from soil, climatic, crop-management and irrigation variables. The predicted values are then used by a Genetic Algorithm to explore a large search space of seasonal crop combinations. The best candidate strategies generated by GA are transferred to PSO, which refines the solutions using personal-best and global-best learning. The optimization objective is formulated to maximize crop yield and economic profit while minimizing irrigation water requirement. The final decision-support output consists of a recommended seasonal crop combination, predicted yield, expected profit and water requirement. The proposed modular framework is intended for sustainable agricultural planning and can be adapted to different soil types, climatic conditions, seasons and irrigation environments. The framework provides a structured computational approach for integrating prediction and multi-objective optimization in precision agriculture.

Keywords: Neuro-EvoSwarm Optimizer, Deep Learning, Genetic Algorithm, Particle Swarm Optimization, Multicropping, Drip Irrigation, Precision Agriculture

INTRODUCTION

Agricultural decision-making is influenced by interacting soil, climate, crop and resource-management variables. In seasonal multi cropping systems, selecting an appropriate crop combination is more complex than selecting a single crop because productivity, profitability and water demand must be considered simultaneously. Drip irrigation can improve water-use efficiency, but effective crop planning still requires an intelligent method for matching crop choices with soil and climatic conditions. Conventional planning approaches may rely on historical averages, expert judgement or independent optimization of a single objective. Such approaches may not adequately represent nonlinear relationships between environmental variables, crop management and economic outcomes. Machine learning can learn complex relationships from agricultural data, while evolutionary and swarm-based optimization methods can search large decision spaces. The proposed Neuro-EvoSwarm Optimizer (NESO) combines these capabilities. Deep Learning is used as a predictive layer for estimating crop yield and expected economic profit. Genetic Algorithm is used to explore candidate seasonal multi cropping strategies, and Particle Swarm Optimization is used to refine the best GA solutions. Thus, prediction and optimization are integrated into one decision-support framework. The main objectives of the proposed work are: (i) to develop a unified agricultural data-processing and prediction framework; (ii) to estimate crop yield and economic profit using Deep Learning; (iii) to generate and evaluate seasonal multi cropping strategies using GA; (iv) to refine promising solutions using PSO; and (v) to balance productivity, profitability and irrigation-water requirements under drip irrigation.

MATERIALS AND METHODS

Agricultural Data Representation

The framework considers agricultural attributes representing soil, climate, crop management and irrigation conditions. The major variables include soil type, soil pH, organic carbon, clay percentage, maximum temperature, minimum temperature, rainfall, relative humidity, season, crop type, nitrogen, phosphorus, potassium and irrigation water usage. The target variables are total crop yield and total economic profit.

- Soil variables: soil type, soil pH, soil organic carbon and clay percentage.
- Climate variables: maximum temperature, minimum temperature, rainfall and relative humidity.
- Crop-management variables: season, crop type and fertilizer application (N, P and K).
- Resource variable: irrigation water usage.
- Optimization targets: crop yield, economic profit and irrigation-water requirement.

Data Preprocessing

Before model training, the agricultural data are processed to improve consistency and numerical stability. The preprocessing pipeline includes missing-value handling, detection of inconsistent records and outliers, categorical encoding, feature scaling and normalization. Relevant features are subsequently selected for model development.

Feature selection focuses on variables that are expected to have a meaningful influence on crop performance, including climatic conditions, fertilizer application, irrigation-water usage and seasonal information. The resulting feature set is supplied to the prediction module.

Deep Learning Prediction Module

The Deep Learning module learns nonlinear relationships between agricultural input variables and the target variables. For each candidate agricultural condition, the model estimates expected crop yield and expected economic profit. These predictions are used as fitness information during optimization.

Conceptually, the prediction function can be represented as:

$\hat{y} = f\theta(X)$

where X represents the selected agricultural input features, $f\theta$ represents the trained Deep Learning model, and $\hat{y}$ represents the predicted agricultural outcome.

Genetic Algorithm Optimization

The Genetic Algorithm represents a seasonal multi cropping strategy as a chromosome. An initial population of candidate strategies is generated and evaluated. Selection, crossover and mutation are applied to produce new candidate solutions. Low-quality strategies are progressively eliminated, while high-quality strategies are retained.

The fitness function is designed as a multi-objective measure. A general weighted formulation is:

$$F = w_1Y + w_2P - w_3W$$

where Y is predicted yield, P is predicted economic profit, W is irrigation-water requirement, and w_1, w_2 and w_3 are user-defined weights. Higher fitness indicates a more desirable balance between productivity, profitability and water use.

Particle Swarm Optimization Refinement

The best candidate strategies obtained from GA are used to initialize the PSO search. Each particle represents a candidate crop-allocation strategy. Particles update their positions based on their personal best solution and the global best solution identified by the swarm. This refinement stage is intended to improve the quality of promising GA solutions and accelerate convergence toward a high-quality solution.

The conceptual PSO update is represented by:

$v_i(t+1) = \omega v_i(t) + c_1r_1[pbest_i - x_i(t)] + c_2r_2[gbest - x_i(t)]$

$x_i(t+1) = x_i(t) + v_i(t+1)$

where x_i is the particle position, v_i is particle velocity, $pbest_i$ is the personal best, gbest is the global best, ω is the inertia weight, c_1 and c_2 are learning coefficients, and r_1 and r_2 are random values in [0,1].

NESO Workflow

- Load the agricultural dataset.
- Clean, encode, scale and normalize the data.
- Select relevant agricultural features.
- Train the Deep Learning prediction model.
- Generate candidate seasonal multi cropping strategies.
- Evaluate candidate strategies using predicted yield, profit and water use.
- Apply GA selection, crossover, mutation and replacement.
- Transfer the best GA solutions to PSO.
- Refine the candidate strategies using personal-best and global-best learning.
- Select the final strategy satisfying the optimization objectives.
- Report recommended crop combination, predicted yield, expected profit and irrigation-water requirement.

RESULTS AND DISCUSSION

The consolidated framework produces a decision-support pipeline in which prediction and optimization are connected. The Deep Learning stage supplies predicted crop-performance and economic information to the optimization stages. GA provides broad exploration of possible seasonal crop combinations, while PSO provides a refinement mechanism for the best solutions obtained from GA. The framework is designed to evaluate three principal agricultural objectives: maximizing crop yield, maximizing economic profit and minimizing irrigation-water requirement. This makes the method suitable for situations in which a farmer or planner must balance production and economic outcomes with water conservation. The proposed architecture also supports adaptability. Soil characteristics, climatic conditions, crop types, fertilizer levels and irrigation practices can be modified according to the target agricultural region. The modular structure allows the prediction and optimization components to be updated independently when additional data become available. Importantly, the present consolidated manuscript describes the NESO methodology and decision-support framework. Exact numerical performance values, comparative experiments and statistical significance should be reported only after the final experimental runs are completed. This avoids presenting unverified numerical results.

Advantages of the Proposed Neso Framework

- Integrated prediction and optimization: Deep Learning, GA and PSO are combined in a single workflow.
- Nonlinear prediction: Deep Learning can model complex relationships among soil, climate and crop-management variables.
- Large search capability: GA can explore a broad space of seasonal crop combinations.
- Solution refinement: PSO refines promising GA solutions using cooperative swarm intelligence.
- Multi-objective planning: yield, profit and irrigation-water use are considered together.
- Water-aware crop planning: irrigation requirement is explicitly included in the optimization objective.
- Adaptability: the framework can be applied to different seasons, soils, climatic conditions and irrigation settings.
- Decision support: the final output is presented as a practical crop-planning recommendation.

Limitations and Future Work

The quality of the final recommendations depends on the quality, representativeness and completeness of the agricultural data used for training and optimization. Further validation using larger real-world datasets and field-level observations is required before deployment as an operational farm decision-support system. Future work will focus on validating NESO using multi-season and multi-location agricultural datasets, comparing NESO with individual DL, GA and PSO approaches using common evaluation metrics, incorporating additional water and soil constraints, and developing a practical farmer-oriented decision-support interface.

CONCLUSION

This paper presents the Neuro-EvoSwarm Optimizer (NESO), a hybrid Deep Learning–Genetic Algorithm–Particle Swarm Optimization framework for seasonal multi cropping strategy optimization under drip irrigation. The framework integrates agricultural data preprocessing, prediction, evolutionary search and swarm-based refinement. Deep Learning estimates crop yield and economic profit, GA explores candidate seasonal crop combinations, and PSO refines the best solutions. By jointly considering crop productivity, economic profitability and irrigation-water requirement, NESO provides a structured approach to intelligent agricultural planning. The modular architecture makes the framework adaptable to different agricultural environments and suitable for future precision-agriculture applications. Experimental validation with complete numerical results and real-world field data will strengthen the practical evidence for the proposed model.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this research work.

Data Availability

The agricultural data and implementation details used for model development will be made available by the corresponding author upon reasonable request, subject to applicable institutional and research-use conditions.

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Table 1: Agricultural variables considered in the NESO framework

Category	Variables
Soil	Soil type; soil pH; soil organic carbon; clay percentage
Climate	Rainfall; maximum temperature; minimum temperature; humidity
Crop & season	Season; crop type
Fertilizer	Nitrogen (N); phosphorus (P); potassium (K)
Irrigation	Water usage under drip irrigation
Outputs	Total yield; total economic profit

Table 2: Role of the three computational components in NESO

Component	Primary role	Output
Deep Learning	Predict crop yield and economic profit	Predicted outcomes
Genetic Algorithm	Explore seasonal multi cropping strategies	Promising candidates
Particle Swarm Optimization	Refine promising candidates	Final optimized strategy

Table 3: Optimization objectives and interpretation

Objective	Direction	Interpretation
Crop yield	Maximize	Higher expected production
Economic profit	Maximize	Higher expected economic return
Irrigation water use	Minimize	Improved water-use efficiency
Overall fitness	Maximize	Balanced agricultural decision

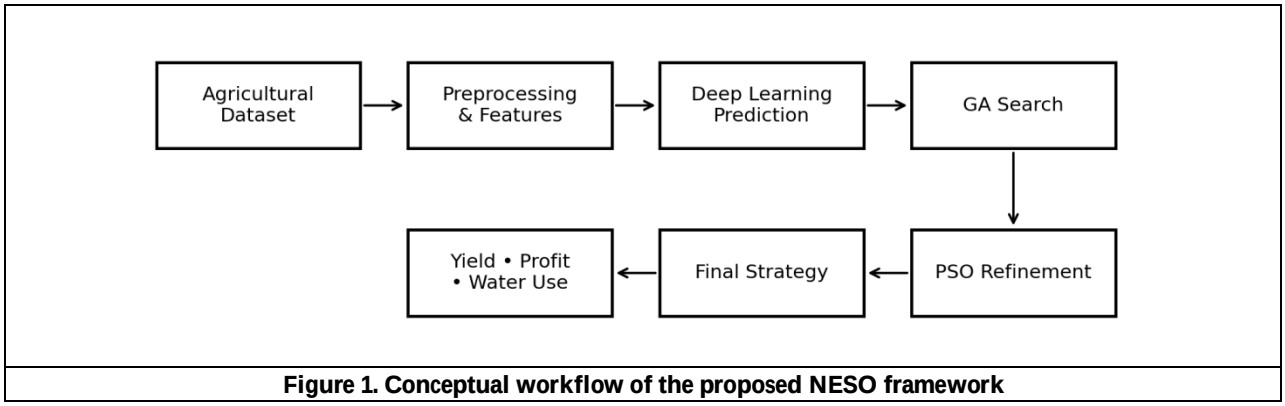

Figure 1. Conceptual workflow of the proposed NESO framework

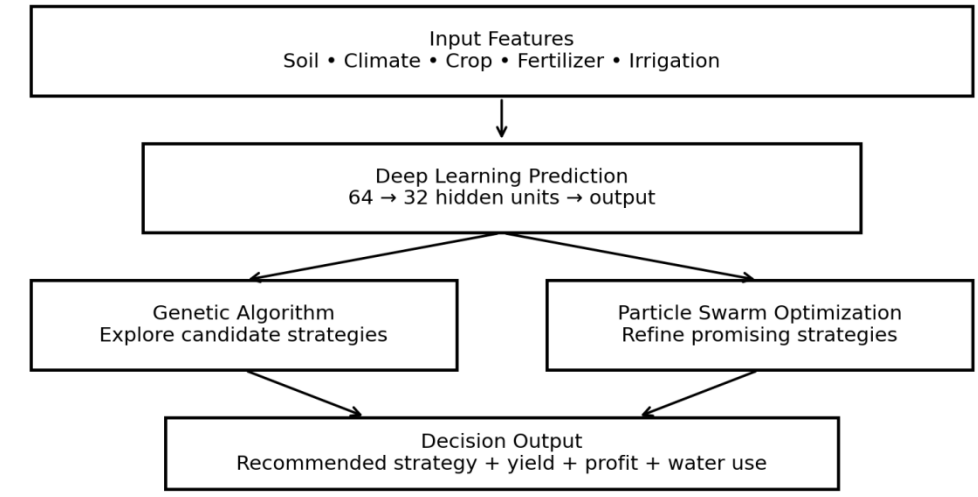

Figure 2. NESO Model Architecture

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