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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: Agricultural planning under variable soil and climatic conditions requires simultaneous consideration of productivity, profitability and limited irrigation resources. 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) for seasonal multicropping strategy optimization under drip irrigation. The framework uses soil characteristics, climatic variables and crop-management information to predict crop yield and economic profit and then searches for high-quality crop combinations. Data preprocessing includes missing-value handling, outlier detection, categorical encoding, feature scaling and normalization. The Deep Learning component learns nonlinear relationships between agricultural conditions and target outcomes. GA provides broad evolutionary exploration through population initialization, fitness evaluation, selection, crossover, mutation and replacement, while PSO refines the best GA solutions using personal-best and global-best information. A multi-objective fitness formulation is used to maximize yield and profit while minimizing irrigation water use. The source document describes the model architecture, workflow, training configuration and decision-support outputs, but does not provide a complete set of numerical test results; therefore, this condensed paper does not fabricate accuracy or optimization values. The framework provides a scalable basis for precision agriculture and can be extended with real-time IoT observations, weather forecasts, GIS and additional sustainability indicators.

Keywords: seasonal multicropping; drip irrigation; Deep Learning; Genetic Algorithm; Particle Swarm Optimization; NESO; crop yield prediction; agricultural decision support; water-use efficiency

1. INTRODUCTION

Agricultural decision-making has become increasingly complex because crop performance is influenced by interacting soil, climatic, irrigation and management variables. Climate variability, water scarcity, soil degradation and the need to improve farm profitability require planning methods that can evaluate several objectives simultaneously. Seasonal multicropping adds another level of complexity because crop combinations must be compatible with season, soil, climate, water availability and nutrient requirements.

Drip irrigation provides water directly to the crop root zone and can improve water-use efficiency. However, efficient irrigation alone does not determine which seasonal crop combination will provide the best balance between yield, profit and water consumption. Conventional decisions based mainly on experience and manual analysis are difficult to scale when many agricultural variables and possible crop combinations are considered.

The source study proposes a hybrid framework combining DL, GA and PSO. DL serves as the prediction engine; GA explores a broad search space of candidate seasonal crop combinations; and PSO refines the best GA solutions. The framework therefore connects prediction with optimization rather than treating them as independent tasks. The major research contributions identified in the source are the integrated hybrid framework, a preprocessing pipeline, prediction of crop yield and profit, multi-objective optimization and intelligent crop recommendations.

The remainder of this paper presents the research gap, data and methodology, the NESO architecture, mathematical formulation, implementation configuration, results supported by the source document, limitations and future enhancements.

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2. RELATED WORK AND RESEARCH GAP

2.1 Deep Learning for Agricultural Prediction

Deep Learning can model nonlinear relationships among soil properties, temperature, rainfall, humidity, fertilizer application, irrigation and crop performance. In the proposed framework, the prediction module estimates crop yield and economic profit from preprocessed agricultural features. The source emphasizes that prediction alone is insufficient because it does not directly select the optimal crop combination.

2.2 Genetic Algorithm for Crop Optimization

GA uses a population of candidate solutions and evolutionary operators to explore a large search space. In the proposed framework, each chromosome represents a seasonal multicropping strategy. Fitness is based on predicted yield, predicted profit and irrigation water use. Selection, crossover, mutation and replacement progressively improve the candidate population.

2.3 Particle Swarm Optimization for Refinement

PSO represents candidate solutions as particles and updates them using each particle's personal best and the swarm's global best. The source uses the best GA chromosomes as the initial PSO particles, reducing the need to begin the refinement stage from random solutions. This hybridization is intended to improve convergence and solution quality.

2.4 Research Gap

The source identifies five principal gaps: (i) prediction and optimization are often treated separately; (ii) many models use a single objective; (iii) seasonal multicropping under drip irrigation has received comparatively less attention than single-crop optimization; (iv) relatively few approaches combine DL, GA and PSO in one decision-support framework; and (v) agricultural decision-support systems need better adaptability across changing soil and climatic conditions.

3. MATERIALS AND METHODOLOGY

3.1 Agricultural Variables

The framework organizes variables into soil, climate and crop-management groups. Soil variables are soil type, soil pH, organic carbon and clay percentage. Climate variables are maximum temperature, minimum temperature, rainfall and relative humidity. Crop-management variables are season, crop name, nitrogen, phosphorus, potassium and water usage. The target variables are total crop yield and total economic profit.

Category	Variables	Role
Soil	Soil type, pH, organic carbon, clay %	Suitability, fertility and water retention
Climate	Tmax, Tmin, rainfall, humidity	Seasonal growth and water demand
Crop management	Season, crop, N, P, K, water usage	Cultivation and resource management
Targets	Total yield, total profit	Prediction and optimization outcomes

3.2 Data Preprocessing

The preprocessing stage prepares heterogeneous agricultural records for prediction and optimization. The documented operations are missing-value handling, outlier detection, label encoding, feature scaling and normalization. Categorical variables such as soil type, crop name and season are converted into numerical representations. Scaling and normalization reduce differences in measurement units so that large-valued variables do not dominate model training.

3.3 Deep Learning Prediction Module

The source describes a Deep Neural Network using agricultural input features to predict crop yield and crop profit. The documented training configuration uses ReLU activation in hidden layers, a linear output, Adam optimization, Mean Squared Error loss, batch size 32 and 50 epochs. Evaluation metrics specified in the source are MAE, RMSE and R^2.

Parameter	Configuration
Model	Deep Neural Network
Input variables	14 documented agricultural features
Hidden layers	2–3
Activation	ReLU
Output	Linear

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Optimizer	Adam
Loss	MSE
Batch size	32
Epochs	50
Metrics	MAE, RMSE, R^2

3.4 Hybrid NESO Architecture

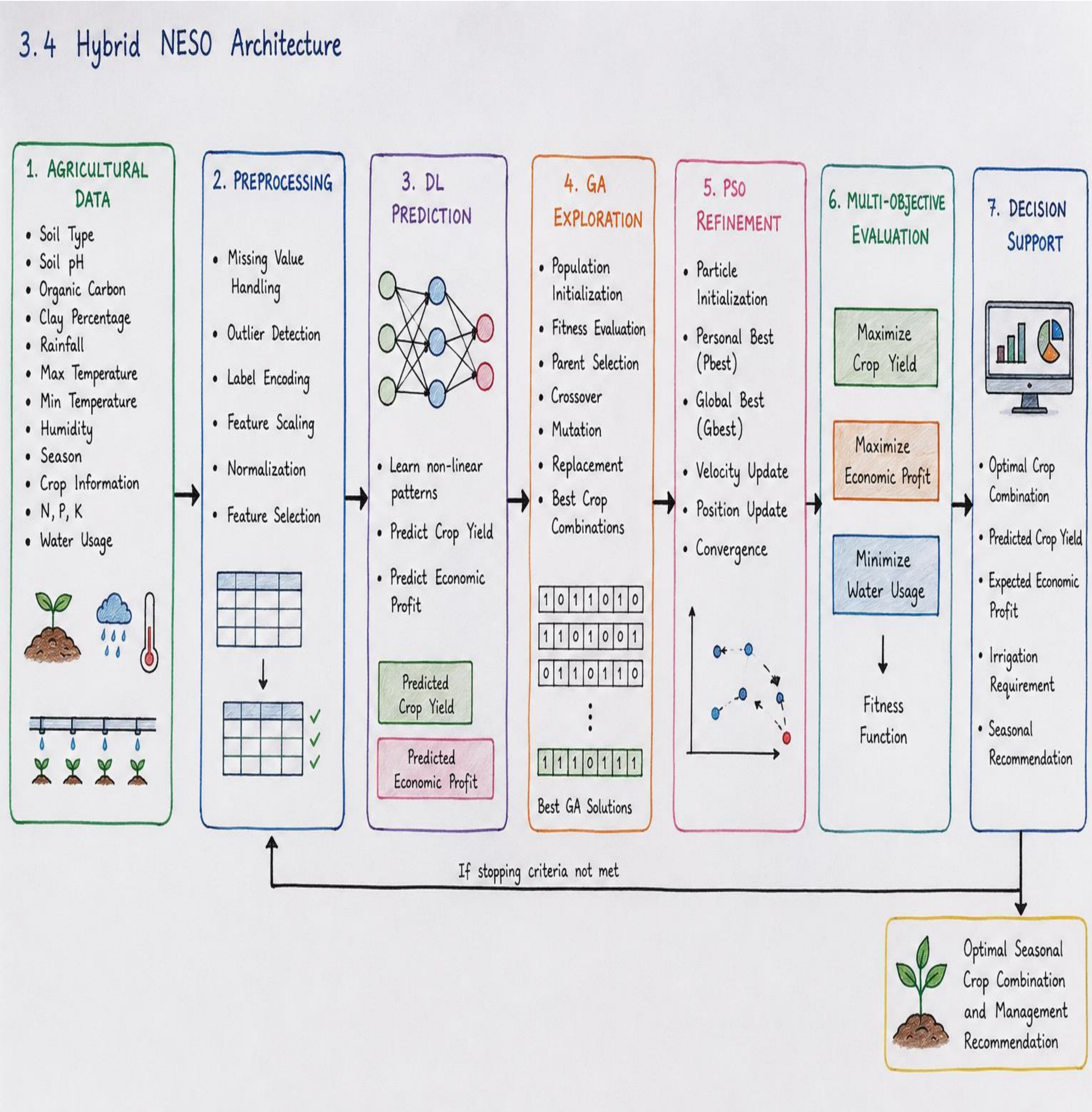

Figure 1. Condensed workflow of the proposed NESO framework.

4. PROPOSED NESO ALGORITHM

The hybrid process begins with agricultural data loading and preprocessing. Relevant features are supplied to the DL model, which predicts yield and profit. GA then creates feasible seasonal crop combinations and evaluates them using a

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multi-objective fitness function. The highest-quality chromosomes are transferred to PSO as initial particles. PSO updates each particle using its personal best and the global best until the stopping condition is reached. The final particle is converted into an agricultural recommendation.

4.1 Chromosome and Particle Representation

A chromosome represents one seasonal multicropping strategy. Example representations in the source include combinations such as Tomato | Onion | Cowpea | Groundnut and Maize | Chilli | Green Gram | Tomato. In the PSO stage, each selected chromosome becomes a particle containing the crop combination, predicted yield, predicted profit, water requirement and fitness value.

4.2 Multi-objective Fitness Function

The optimization objective is to maximize yield and profit while minimizing irrigation water. A normalized weighted formulation consistent with the stated objectives can be written as:

$$\mathbf{Fitness} = w_{\gamma} \cdot Y\_norm + w_{p} \cdot P\_norm - w_{w} \cdot W\_norm$$

where Y_norm is normalized predicted yield, P_norm is normalized predicted profit, W_norm is normalized irrigation water use, and w_{γ}, w_{p} and w_{w} are user-defined objective weights. The source specifies the three objectives but does not report fixed numerical weights; hence no specific weight values are assumed here.

4.3 Genetic Algorithm Procedure

1. Initialize a feasible population of seasonal crop combinations.
2. Predict yield and profit for candidate solutions using the DL model.
3. Evaluate fitness using yield, profit and water consumption.
4. Select high-fitness parents.
5. Apply crossover to generate new combinations.
6. Apply mutation to maintain diversity and explore new combinations.
7. Replace poorer solutions and retain strong chromosomes.
8. Repeat until the GA stopping criterion is satisfied.
9. Transfer the best chromosomes to PSO.

4.4 Particle Swarm Refinement

PSO starts from the high-quality GA chromosomes rather than a completely random population. During each iteration, particles evaluate their current solutions, update personal bests, identify the global best, and move toward promising regions of the search space. The process stops when the maximum iteration count is reached, the global best stops improving, fitness becomes stable, or an acceptable crop combination is identified.

5. EXPERIMENTAL CONFIGURATION AND EVALUATION

The source specifies a methodology-oriented experimental configuration but does not provide a complete numerical results table. The evaluation design therefore focuses on the documented model components and output measures. A complete empirical study should report training/test split, dataset size and provenance, random seeds, GA population size, number of generations, crossover and mutation rates, PSO swarm size, inertia and acceleration coefficients, convergence curves, and baseline comparisons.

Component	Documented configuration	Evaluation output
DL	Adam, MSE, ReLU, batch 32, 50 epochs	MAE, RMSE, R^2; predicted yield/profit
GA	Population-based evolutionary search	Best candidate chromosomes and fitness
PSO	GA solutions used as initial particles	Best particle, fitness, yield, profit, water
NESO	DL + GA + PSO	Final seasonal crop recommendation

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6. RESULTS AND DISCUSSION

The source document supports the conclusion that the proposed architecture provides a unified prediction-and-optimization workflow. DL supplies predicted yield and economic profit; GA explores a diverse set of feasible crop combinations; and PSO refines the strongest GA solutions. The intended final outputs are an optimal seasonal crop combination, maximum predicted yield, maximum economic profit, minimum irrigation water requirement and an intelligent farming recommendation.

The framework has a clear division of responsibilities. The predictive stage handles nonlinear relationships among agricultural variables, while the evolutionary and swarm stages search the decision space. Starting PSO from high-quality GA solutions is expected to reduce search effort compared with independent random initialization. However, these are methodological advantages described by the source, not measured percentage improvements.

Importantly, the supplied 78-page document does not contain a complete numerical results section with validated MAE/RMSE/R^2 values, final crop combinations, water savings, or statistical comparison against GA-only, PSO-only or DL-only baselines. Such values should be added only after the actual experimental runs are completed. This avoids presenting unsupported numbers as research findings.

6.1 Recommended Comparative Evaluation

Model	Prediction	Search	Refinement	Primary comparison
DL	Yes	No	No	Prediction quality
GA	Uses prediction	Yes	No	Exploration and fitness
PSO	Uses prediction	Yes	Yes	Convergence/refinement
GA–DL	Yes	Yes	No	Integrated prediction + exploration
NESO (GA–DL–PSO)	Yes	Yes	Yes	Overall multi-objective performance

7. CONCLUSION

This paper presents the NESO hybrid framework for seasonal multicropping strategy optimization under drip irrigation. The approach integrates Deep Learning, Genetic Algorithm and Particle Swarm Optimization into a single decision-support pipeline. Soil, climate and crop-management information is preprocessed and supplied to the predictive model, whose outputs are then used by GA and PSO to search for crop combinations that balance productivity, profitability and water use.

The principal value of the framework is the integration of prediction and optimization. Rather than stopping at crop-yield prediction, the system continues to an explicit decision stage. GA provides broad exploration and PSO provides refinement, while the multi-objective formulation reflects the practical need to consider yield, profit and irrigation simultaneously. The supplied source provides a strong methodological foundation, but additional experimental evidence is required before quantitative claims about accuracy, water savings or superiority over baseline algorithms can be made.

8. FUTURE ENHANCEMENT

Future development identified in the source includes real-time IoT sensor integration; short- and long-term weather forecasting; additional variables such as pest and disease occurrence, solar radiation, groundwater availability and market prices; farmer-friendly web or mobile applications; GIS integration; extension to other irrigation systems; advanced AI such as reinforcement learning, transformers and explainable AI; large-scale multi-regional validation; and economic/environmental indicators such as water-use efficiency, carbon footprint, energy use and greenhouse-gas emissions.

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