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Neuro-Evo Swarm Optimizer (NESO Model): A hybrid Deep Learning, Genetic Algorithm and Particle Swarm Optimization model for Multicropping Strategy Optimization across Irrigation Systems

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Abstract
This study presents the development of an intelligent algorithm for optimizing seasonal multicropping systems under drip irrigation. The proposed algorithm is designed to support agricultural decision-making by integrating agricultural data preprocessing, predictive analysis, optimization, and decision support into a unified framework. The algorithm processes multiple input parameters, including soil characteristics (soil type, soil pH, organic carbon, and clay percentage), climatic conditions (maximum and minimum temperature, rainfall, and humidity), and crop management factors such as season, crop type, fertilizer application (N, P, and K), and irrigation water usage.
The algorithm begins with data preprocessing, where missing values are handled, inconsistent records are corrected, categorical variables are encoded, and numerical attributes are normalized to improve data quality. Relevant features influencing crop performance are then extracted and used to train a prediction model that estimates crop yield and expected economic profit. Based on these predictions, an optimization module iteratively generates and evaluates candidate seasonal crop combinations using a multi-objective fitness function. The fitness evaluation simultaneously considers crop productivity, economic profitability, and irrigation water requirements to identify the most suitable cropping strategy under drip irrigation conditions.
The algorithm continues the optimization process until the stopping criterion is satisfied, after which the best-performing crop combination is selected. The final output includes the recommended seasonal crop combination, predicted crop yield, estimated economic profit, and required irrigation water. The proposed algorithm provides an efficient decision-support mechanism for sustainable agricultural planning by balancing productivity, profitability, and resource conservation.
The modular design of the algorithm enables scalability and adaptability to different agricultural datasets and climatic conditions, making it suitable for precision agriculture applications. By integrating prediction and optimization within a single intelligent framework, the proposed approach contributes to improved seasonal crop planning, efficient water management, and sustainable farming practices.

Keywords: Principle of the hybrid algorithm, 4 significance of the Hybrid GA–DL–PSO Algorithm, advantages of the Hybrid GA–DL–PSO model

Introduction
The proposed Hybrid Genetic Algorithm–Deep Learning–Particle Swarm Optimization (GA–DL–PSO) algorithm integrates the strengths of Deep Learning (DL), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) to develop an intelligent decision-support framework for seasonal multicropping under drip irrigation. The integration of these three techniques overcomes the limitations of using any single algorithm independently.
Deep Learning provides highly accurate predictions of crop yield and economic profit by learning complex relationships between soil properties, climatic conditions, and crop management practices. However, Deep Learning alone cannot determine the optimal crop combination. The Genetic Algorithm addresses this limitation by generating and evaluating multiple candidate crop allocation strategies using evolutionary search techniques. Although GA efficiently explores a wide search space, it may converge slowly or become trapped in near-optimal solutions. Therefore, Particle Swarm Optimization is incorporated as the final optimization stage to refine the best solutions generated by GA and identify the global optimum.
The hybrid framework combines the predictive capability of Deep Learning with the global search ability of the Genetic Algorithm and the rapid convergence characteristics of Particle Swarm Optimization. This integrated approach improves prediction accuracy, optimization efficiency, and the quality of the final crop recommendation.

Working Principle of the Hybrid Algorithm
The proposed hybrid algorithm consists of four major stages:
- Agricultural Data Processing
- Deep Learning Prediction
- Genetic Algorithm Optimization
- Particle Swarm Optimization Refinement

Each stage performs a specific function within the intelligent decision-making framework.

Stage 1: Agricultural Dataset Loading
The algorithm begins by loading the agricultural dataset collected from historical cultivation records. The dataset contains comprehensive information related to:

Soil Parameters
- Soil Type
- Soil pH
- Organic Carbon
- Clay Percentage

Climate Parameters
- Maximum Temperature
- Minimum Temperature
- Rainfall
- Relative Humidity

Crop Parameters
- Season
- Crop Name
- Nitrogen
- Phosphorus
- Potassium
- Water Usage

Target Variables
- Total Yield
- Total Profit

These variables provide the knowledge required for prediction and optimization.

Stage 2: Data Preprocessing

After loading the dataset, preprocessing is performed to improve data quality before model training.

The preprocessing stage includes
- Outlier detection
- Label encoding
- Feature scaling
- Data normalization

The purpose of preprocessing is to eliminate inconsistencies, improve data quality, and prepare the dataset for Deep Learning training.

A clean dataset significantly improves prediction accuracy.

Stage 3: Feature Selection

The preprocessing module generates numerous agricultural variables. However, not all Feature selection identifies the most relevant agricultural attributes that significantly influence crop productivity.

The selected features include
- Climatic conditions
- Fertilizer application
- Irrigation water usage
- Seasonal information

Selecting important features reduces computational complexity while improving model performance.

Stage 4: Deep Learning Prediction

The selected features are supplied to the Deep Learning model.

The prediction model learns hidden nonlinear relationships among agricultural variables and predicts
- Expected Crop Yield
- Expected Economic Profit

The predicted outputs become the evaluation criteria for the optimization algorithms.

Accurate prediction enables the optimization module to identify economically beneficial crop combinations.

Stage 5: Genetic Algorithm Optimization

The Genetic Algorithm receives the predicted yield and profit values from the Deep Learning module.

Initially, multiple candidate crop combinations are generated.

Each chromosome represents one seasonal multicropping strategy.

The optimization process consists of
- Fitness Evaluation
- Parent Selection
- Crossover
- Mutation
- Replacement

During every generation, poor-performing crop combinations are discarded, while high-ping combinations are retained.

The evolutionary process gradually improves the quality of candidate solutions.

The output of the Genetic Algorithm consists of the best-performing chromosomes.

Stage 6: Particle Swarm Optimization

The best chromosomes obtained from the Genetic Algorithm become the initial particles for Particle Swarm Optimization.

Instead of searching randomly, PSO begins with already optimized solutions.

Each particle improves its crop allocation strategy by learning from
- Personal Best solution
- Global Best solution

The swarm gradually converges toward the globally optimal crop combination.

PSO further improves
- Crop Yield
- Economic Profit
- Water Efficiency

This refinement stage increases optimization accuracy.

Stage 7: Final Decision Support

After PSO converges, the best-performing particle becomes the final solution.

The intelligent decision-support module displays
- Recommended Crop Combination
- Predicted Crop Yield
- Expected Economic Profit
- Water Requirement

These recommendations assist farmers in selecting suitable seasonal multicropping strategies under drip irrigation.

Output of the Hybrid Framework

The proposed hybrid framework produces the following outputs:

- Optimal seasonal crop combination
- Maximum predicted crop yield
- Maximum economic profit
- Minimum irrigation water requirement
- Intelligent recommendation for sustainable farming

These outputs provide scientific support for agricultural decision-making.

Significance of the Hybrid GA–DL–PSO Algorithm

The hybrid framework combines prediction and optimization into a single intelligent decision-support system.

Deep Learning performs accurate prediction.

Genetic Algorithm explores diverse crop allocation strategies.

Particle Swarm Optimization refines the best solutions to identify the global optimum.

The integration of these three techniques provides better performance than using any individual algorithm independently.

Advantages of the Hybrid GA–DL–PSO Model

The proposed hybrid intelligent framework offers several advantages over conventional agricultural decision-making methods.

1. **Accurate Prediction of Crop Yield and Economic Profit**

The Deep Learning model effectively learns complex nonlinear relationships among soil properties, climatic conditions, irrigation practices, fertilizer application, and crop management. As a result, it provides highly accurate predictions of crop yield and economic profit. These reliable predictions form the basis for the subsequent optimization process.

2. **Efficient Exploration of Crop Combinations**

The Genetic Algorithm efficiently explores a large search space by generating multiple candidate seasonal crop combinations. Through evolutionary operations such as selection, crossover, and mutation, GA identifies promising solutions without exhaustively evaluating every possible combination.

3. **Rapid Convergence toward the Global Optimum**

Particle Swarm Optimization receives the best-performing solutions from the Genetic Algorithm and refines them using cooperative swarm intelligence. This enables the optimization process to converge rapidly toward the global optimum while avoiding poor local solutions.

4. **Multi-Objective Optimization**

The proposed framework simultaneously considers multiple agricultural objectives, including:

- Maximization of crop yield.
- Maximization of economic profit.
- Minimization of irrigation water usage.
- Improvement of resource utilization.

This multi-objective capability makes the framework suitable for sustainable agricultural planning.

5. **Improved Water Management**

Efficient utilization of irrigation water is one of the primary objectives of the proposed framework. By incorporating water usage into the optimization process, the system recommends crop combinations that maximize productivity while reducing water consumption under drip irrigation systems.

6. **Adaptability to Diverse Agricultural Conditions**

The framework can easily adapt to different:

- Soil types
- Climatic regions
- Seasonal cropping systems
- Fertilizer management practices
- Irrigation methods

This flexibility allows the framework to be applied in various agricultural environments.

7. **Scalability and Computational Efficiency**

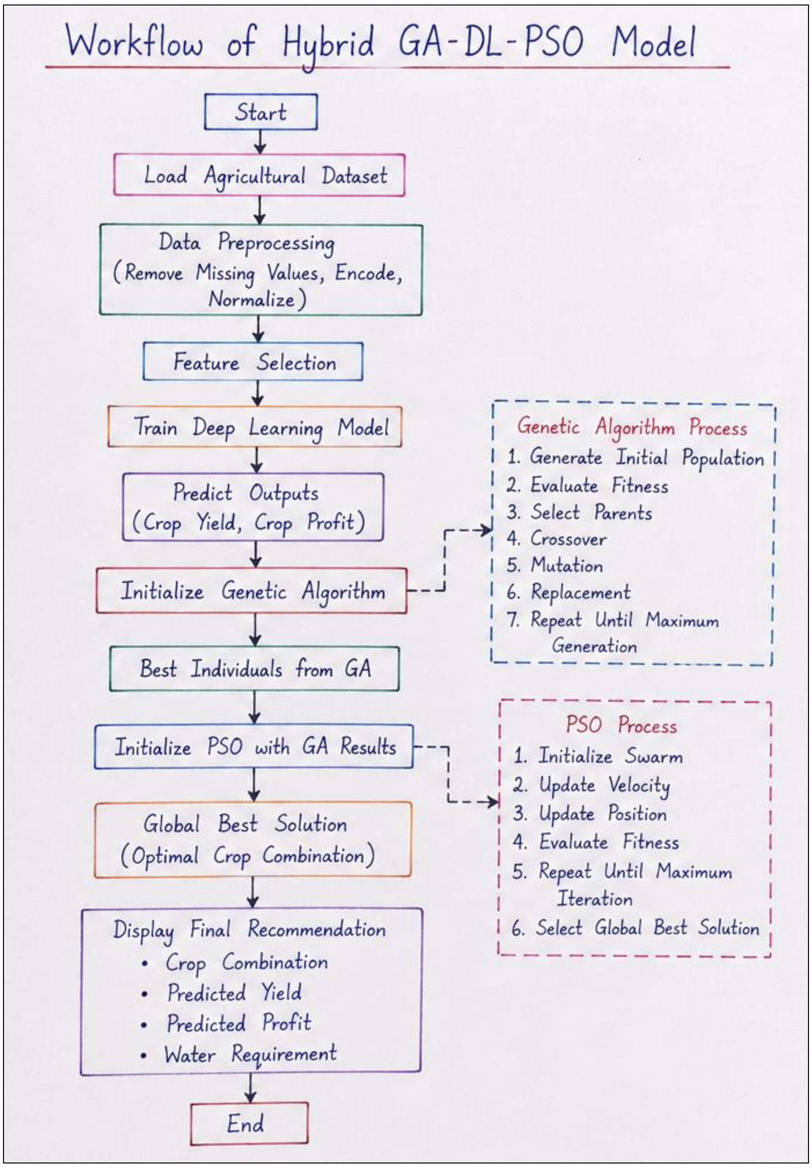
The proposed model is scalable and can process large agricultural datasets containing numerous crop combinations and environmental variables. The hybrid integration reduces computational complexity by allowing each algorithm to perform the task for which it is best suited.

8. **Intelligent Decision Support for Farmers**

The framework functions as an intelligent decision-support system by providing scientifically validated recommendations. Farmers can use these recommendations to select the most suitable seasonal crop combinations, improve productivity, increase profitability, and utilize water resources more efficiently.

9. **Contribution to Sustainable Agriculture**

By optimizing crop selection, maximizing resource utilization, and reducing unnecessary water consumption, the proposed hybrid framework supports the principles of precision agriculture and sustainable farming. It enables informed agricultural decision-making while promoting environmental conservation and long-term farm productivity.



Summary of the Hybrid Model

The proposed GA–DL–PSO hybrid framework integrates the predictive capabilities of Deep Learning, the evolutionary search mechanism of the Genetic Algorithm, and the refinement efficiency of Particle Swarm Optimization into a unified intelligent decision-support system. Deep Learning accurately predicts crop yield and economic profit using historical agricultural data, the Genetic Algorithm generates and optimizes diverse seasonal crop combinations, and Particle Swarm Optimization refines these solutions to obtain the global optimum. The resulting framework provides farmers with optimal crop recommendations that maximize yield and profitability while minimizing irrigation water consumption under drip irrigation. Its adaptability, scalability, and multi-objective optimization capability make it a robust solution for precision agriculture and sustainable seasonal multicropping systems.

Conclusion

The proposed Hybrid Genetic Algorithm–Deep Learning–Particle Swarm Optimization (GA–DL–PSO) framework provides an intelligent and efficient approach for optimizing seasonal multicropping systems under drip irrigation. The framework integrates the predictive capability of Deep Learning, the evolutionary search mechanism of the Genetic Algorithm, and the refinement capability of Particle Swarm Optimization to recommend the most suitable crop combinations for sustainable agricultural production.

Initially, the agricultural dataset containing soil characteristics, climatic conditions, crop management practices, and historical cultivation records is preprocessed to improve data quality. The Deep Learning model is then trained using the preprocessed dataset to accurately predict crop yield and economic profit. These predictions provide the basis for evaluating different seasonal crop combinations. The Genetic Algorithm explores a large search space by generating diverse candidate crop combinations and optimizing them through population initialization, fitness evaluation, parent selection, crossover, mutation, and replacement operations. The best-performing crop combinations obtained from the Genetic Algorithm are subsequently refined by the Particle Swarm Optimization module. PSO further improves these solutions by utilizing cooperative swarm intelligence, enabling the framework to converge toward the global optimum with higher accuracy and reduced computational effort. the proposed hybrid model simultaneously considers multiple agricultural objectives, including maximizing crop yield, maximizing economic profit, and minimizing irrigation water usage under drip irrigation. This multi-objective optimization approach supports efficient resource utilization while promoting sustainable farming practices.

Overall, the proposed GA–DL–PSO framework demonstrates significant potential as an intelligent decision-support system for precision agriculture. It provides reliable crop recommendations, enhances agricultural productivity, improves farmers' economic returns, conserves irrigation water, and adapts effectively to varying soil types, climatic conditions, and seasonal cropping systems. Therefore, the proposed framework offers a scalable, robust, and practical solution for sustainable seasonal multicropping optimization and contributes to the advancement of intelligent agricultural decision-making.

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