THE SCIENTIFIC TEMPER (2026) Vol. 17 (6): 6367-6387

E-ISSN: 2231-6396, ISSN: 0976-8653

Doi: 10.58414/SCIENTIFICTEMPER.2026.17.6.07

https://scientifictemper.com/

RESEARCH ARTICLE

Adaptive Graph Enhanced Spatio Temporal with Multi-Objective Reinforcement Learning (AGST-MOORL) for Dynamic Fertilizer Optimization

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Abstract

To propose an advanced framework AGST-MOORL to improve fertilizer recommendation accuracy under dynamic agricultural conditions. The primary objective is to overcome the limitations of earlier models by incorporating adaptive learning of spatial relationships, temporal variations, and multi-objective decision optimization. The methodology integrates Adaptive Graph-Based Spatio-Temporal Learning (AGST) with Multi-Objective Reinforcement Optimization (MOORL). Crop Recommendation Dataset with 2480 samples consisting of 22 crop labels, Fertilizer Recommendation Dataset with 150 samples containing fertilizer class for 7 fertilizers and Crop Nutrient Database with 300 crops entries are three datasets used to build our consolidated multi-modal model. They collectively provide us with data about nutrients present in the soil (N, P, K, pH), weather data (taking temperature, humidity and rainfall into account) and nutrients required by each crop. Feature engineering techniques such as Nutrient Deficiency Index (NDI), Rainfall-Temperature Interaction (RTI), and Fertilizer Efficiency Coefficient (FEC) are applied to enrich the data representation. A graph-based structure encodes relationships among samples, while temporal attention mechanisms learn dynamic changes in agricultural conditions across time. The reinforcement learning component further refines recommendations by optimizing trade-offs among yield, cost, and environmental impact. The performance of the proposed AGST-MOORL is assessed using MATLAB and Python for detailed comparative analysis with two baseline models such as Lightweight-CNN, DAEN-MaskRCNN and STLF-MOAFDE. Experimental evaluation demonstrates significant improvement over the previous phase of works. The proposed model achieves 97.2% accuracy, 96.5% precision, 97.0% recall, 96.1% specificity, and 96.7% F1-score, with an enhanced AUC-ROC of 0.78, outperforming existing methods across all metrics. Additionally, convergence speed is improved, and decision stability is enhanced under varying agro-climatic conditions. The proposed work stands as a unified integration of graph-based learning, temporal modeling, and reinforcement-driven multi-objective optimization within a single framework.

Keywords: Graph-Based Spatio-Temporal Learning, Multi-Objective Reinforcement Optimization, Precision Fertilizer Recommendation, Smart Agriculture Analytics, Adaptive Decision-Making Systems

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How to cite this article: Basheer, P., Priya, R. (2026). Adaptive Graph Enhanced Spatio Temporal with Multi-Objective Reinforcement Learning (AGST-MOORL) for Dynamic Fertilizer Optimization. The Scientific Temper, **17**(6):6367-6387.

Doi: 10.58414/SCIENTIFICTEMPER.2026.17.6.07

Source of support: Nil

Conflict of interest: None.

Introduction

Efficient fertilizer management remains a critical challenge in modern agriculture, where decisions must adapt to varying soil conditions, climate fluctuations, and crop-specific nutrient demands. Conventional recommendation systems often rely on static data analysis, which limits their ability to respond to dynamic environmental changes. Recent approaches such as Lightweight-CNN and DAEN-MaskRCNN have improved classification performance by learning feature representations; however, they primarily focus on isolated inputs and lack the ability to capture relationships across samples or evolving conditions over time. As a result, their recommendations may not fully reflect real-world agricultural variability.

The previously developed STLF-MOAFDE, Lightweight CNN and RCNN models addressed part of this limitation by introducing spatio-temporal learning and bio-inspired

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Received: 09/06/2026 **Accepted:** 20/06/2026 **Published:** 25/06/2026

optimization. While it improved prediction accuracy, it still treated data samples independently and relied on a predefined optimization strategy, which restricts adaptability in complex, real-time scenarios. Additionally, the absence of relational learning between similar soil and crop conditions limits its ability to generalize across diverse agricultural environments. To overcome these limitations, this study proposes AGST-MOORL, an adaptive framework that integrates graph-based learning with temporal modeling and reinforcement-driven optimization. The model captures interconnections among samples through graph representation while learning time-dependent variations using attention mechanisms. Furthermore, the reinforcement learning component enables continuous decision refinement by balancing yield, cost, and environmental impact. This unified approach allows the system to move beyond static prediction toward adaptive and context-aware fertilizer recommendation, offering a more practical and scalable solution for precision agriculture.

Recent research highlights significant advancements in smart agriculture through the integration of machine learning and data-driven decision systems. An exploratory survey conducted to emphasize the role of machine learning in predicting climate-smart agricultural practices and supporting sustainable farming decisions. Nevertheless, the study primarily focused on exploratory analysis and did not address real-time adaptability under changing environmental conditions (Freddy Noma et al. 2024). An IoT-driven agricultural framework developed to enable the real-time monitoring of soil and crop conditions, improving resource utilization and field management. Despite these benefits, the framework lacked intelligent decision-making capabilities and adaptive learning mechanisms (Hammad Shahab et al. 2025). Hybrid research demonstrated that ensemble learning techniques can significantly improve agricultural prediction accuracy; however, the approach operated on static datasets and did not effectively capture temporal variations (Liyakathunisa Syed, 2024). A systematic review highlighted the effectiveness of artificial intelligence in crop disease detection, although the reviewed approaches were predominantly image-oriented and did not address fertilizer recommendation or multi-modal data integration (Majdalawieh et al. 2025). Similarly, the capability of deep learning models in recognizing complex patterns are demonstrated well with minor limitations of domain-specific and lacked generalization for agricultural decision-support systems (Nithyanandh & Eldho KJ, 2024).

Further contributions showed that machine learning and deep learning techniques can enhance automation in smart farming environments. Nevertheless, the interaction among soil properties, crop requirements, and environmental factors was not comprehensively modeled (Senthil Kumar Swami Durai & Mary Divya Shamili, 2022). The Paddynet dataset provided a valuable benchmark for fertilizer recommendation research, yet it did not include an integrated framework for intelligent decision optimization (Siddique et al. 2023). In addition, a fog-assisted smart agriculture system proposed for an improved the prediction of soil nutrients and moisture conditions, but its localized learning mechanism limited the modeling of broader spatial relationships and adaptive optimization strategies. Collectively, the existing studies demonstrate notable progress in agricultural intelligence; however, they lack a unified mechanism capable of simultaneously learning spatial relationships, temporal dynamics, and multi-objective decision optimization (Surajit Mohanty et al. 2024). These limitations motivate the development of the proposed AGST-MOORL framework for intelligent and adaptive fertilizer recommendation.

Problem Statement

Existing Accurate fertilizer recommendation remains a complex problem due to the dynamic interaction between soil nutrients, climatic variability, and crop-specific requirements. Existing approaches such as Lightweight-CNN and DAEN-MaskRCNN primarily rely on static feature learning and operate on isolated samples, which limits their ability to capture evolving agricultural conditions. Although the STLF-MOAFDE model introduced spatio-temporal learning and optimization, it still lacks the capability to model relationships among similar data instances and does not fully adapt to changing environmental patterns in real time. This results in suboptimal decisions when applied across diverse farming conditions. The core problem lies in designing a system that can simultaneously learn spatial relationships, temporal variations, and optimize multiple objectives such as yield, cost, and environmental impact. The proposed AGST-MOORL model addresses these limitations by integrating graph-based learning to capture inter-sample dependencies, temporal attention to model evolving conditions, and reinforcement-driven optimization to continuously refine fertilizer decisions. This unified framework ensures adaptive, context-aware, and scalable fertilizer recommendations.

Key Objectives of the Proposed Model

The proposed AGST-MOORL model aims to develop an intelligent fertilizer recommendation system that effectively addresses the dynamic nature of agricultural environments. The first objective is to incorporate graph-based learning to capture hidden relationships among soil properties, crop characteristics, and climatic factors. The second objective focuses on modeling temporal variations by learning how agricultural conditions evolve over time, enabling adaptive decision-making. The third objective is to integrate multi-objective reinforcement optimization

to balance critical factors such as crop yield, fertilizer cost, and environmental sustainability. Additionally, the model aims to improve prediction accuracy and generalization by leveraging enriched feature representations and relational learning. Finally, the system is designed to support real-time deployment, allowing continuous updates and scalable recommendations across different agricultural regions, thereby making it practical for precision farming applications. The following are the key objectives of the proposed deep learning framework.

- To design a graph-based learning framework that captures relationships among soil, crop, and environmental conditions.
- To model temporal variations in agricultural data for adaptive decision-making.
- To optimize fertilizer recommendations by balancing yield, cost, and environmental impact.
- To enhance prediction accuracy and generalization across diverse farming conditions.
- To enable real-time, scalable, and intelligent fertilizer recommendation systems.

The proposed model can be applied in agriculture and smart farming as a decision-support system for precise fertilizer management. Using soil, weather, and crop data collected from sensors or farm records, the model analyzes field conditions and predicts the most suitable fertilizer type, dosage, and timing. Its graph-based learning helps identify similarities across different fields, while temporal modeling captures seasonal and environmental changes. The reinforcement optimization component continuously improves recommendations based on outcomes. This enables farmers to reduce input costs, improve crop yield, and minimize environmental impact, making the system practical for real-time, data-driven, and sustainable farming operations.

Related Works

Current research highlights notable progress in agricultural intelligence through deep learning and optimization techniques. A plant leaf disease detection framework developed by employing Autoencoder Networks (AEN) and Mask R-CNN with multivariable feature selection to improve disease identification accuracy by extracting discriminative features from complex agricultural datasets. Despite its effectiveness, the model remains primarily image-driven and does not extend to multi-modal agricultural decision systems (Selvam & Joy, 2024). An intelligent insecticide and fertilizer recommendation system proposed by employing TPF-CNN to learn feature correlations and enhance recommendation accuracy. Nevertheless, the model relies on static input data and lacks adaptability to temporal environmental variations (Thorat et.al. 2023). Research works demonstrated the potential of machine learning frameworks in precision agriculture for automating crop monitoring & yield prediction. However, these approaches often face challenges in integrating heterogeneous data sources and capturing dynamic interactions among soil, weather, and crop attributes (Shaikh et.al. 2022). Likewise, the smart farming framework presented to emphasize the sustainability and operational efficiency through machine learning, yet the proposed solutions depended on isolated learning models without considering relational or temporal dependencies among agricultural factors (Wang & Li, 2025).

Recent advancements in reinforcement learning have introduced adaptive decision-making capabilities in agriculture. A trust-based multi-objective reinforcement learning model developed for an improvised intelligent farm management by incorporating decision reliability into the learning process. Even so, the framework did not integrate deep feature learning and lacked comprehensive spatio-temporal data representation (Wang et.al. 2026). In the domain of crop disease recognition, a modified lightweight CNN with an attention mechanism that achieved efficient disease classification with reduced computational complexity was proposed. Although effective for visual recognition tasks, the model did not address the recommendation challenges (Liu et.al. 2022). To improve model transparency LIME-based explainable artificial intelligence techniques for crop recommendation systems, enabling local interpretation of prediction outcomes. Nevertheless, these methods focus on explanation rather than improving the predictive capability of the underlying model (Yaganteeswarudu et.al 2025). Furthermore, a combined reinforcement learning with transfer learning to optimize fertilization strategies in paddy cultivation environments. While the approach demonstrated promising optimization performance, its applicability remained restricted to specific agricultural scenarios and lacked generalization across diverse farming conditions (Zhang et al. 2025).

Overall, the existing studies have contributed significantly to disease detection, recommendation systems, explainable artificial intelligence, and optimization techniques. However, most approaches focus on one-dimensional feature analysis, static prediction mechanisms, or isolated optimization strategies. They do not provide a unified framework capable of integrating graph-based relational learning, temporal dependency modeling, and multi-objective adaptive optimization. These limitations motivate the development of the proposed AGST-MOORL framework, which aims to deliver an intelligent, adaptive, and comprehensive fertilizer recommendation system for dynamic agricultural environments. Table 1 presents a detailed analysis of smart farming technologies, fertilizer recommendation approaches, optimization methods, and machine learning and deep learning advancements. The merits and limitations of each study are systematically examined to establish clear research objectives and benchmark the proposed model against existing approaches.

Table 1: Analysis of Related Studies related to Smart Farming, Fertilizer Recommendation and Adaptation of Machine Learning Models

Authors	*Methods Adopted*	*Merits*	*Limitations*
Ali et.al, (2023)	RL-based data dissemination for large-scale smart farming networks, focusing on energy-efficient communication among distributed agricultural IoT nodes.	Useful for smart farming infrastructure because it improves data transfer efficiency, reduces communication overhead, and supports scalable sensor-based monitoring.	The study focuses mainly on data dissemination; fertilizer recommendation, crop nutrient modeling, graph-based learning, and agronomic decision optimization are not addressed.
Cheikhrouhou et.al, (2026)	Explainable federated learning with digital-twin support for privacy-preserving crop recommendation across distributed agricultural data sources.	Strengthens privacy, transparency, and decentralized learning, making it suitable for farms where data sharing is restricted.	The method emphasizes crop recommendation and privacy; fertilizer dosage, temporal nutrient variation, reinforcement-based decision refinement, and cost–environment trade-offs remain limited.
Primantara et.al, (2025)	Machine learning performance analysis for fertilizer industry bagging systems, using model optimization and loss-reduction strategies.	Provides practical insight into fertilizer-industry process improvement and supports predictive quality control through optimized ML models.	The work is industry-process oriented; it does not model field-level soil–crop relationships, temporal agricultural changes, or real-time fertilizer recommendation.
Huang et.al, (2023)	Data-driven machine learning models for soil analysis and evaluation in smart farming, using soil-related variables for predictive assessment.	Directly supports agricultural analytics by improving soil interpretation, feature relevance analysis, and data-driven farm evaluation.	The model stops at soil evaluation; fertilizer type, dosage, timing, graph dependency learning, and multi-objective optimization are not included.
Arshad et.al, (2022)	LoRaWAN-based smart agriculture decision support system for sensor communication, field monitoring, and crop-yield improvement.	Shows the importance of low-power communication and real-time sensing for practical smart farming deployment.	The system is more hardware and communication focused; intelligent fertilizer recommendation, adaptive reinforcement learning, and graph-based agronomic modeling are absent.
Huang et.al, (2023)	Machine learning-based soil property evaluation for smart farming using data-driven analysis and comparative predictive modeling.	Offers a useful baseline for soil-feature interpretation and highlights the role of ML in field condition assessment.	This soil-analysis reference does not extend to integrated fertilizer recommendation, temporal sequence construction, or decision-level optimization.
Nivedita et.al, (2025)	Multi-modal biometric authentication combining complex recognition for security applications.	Demonstrates the value of multi-modal feature fusion and decision-level integration, which can inspire multi-source agricultural fusion.	Limited fertilizer recommendation objective, or crop–soil decision framework.
Omprakash et.al, (2023)	Energy-aware adaptive sleep scheduling and secure data transmission using an improvised firefly bio-inspired algorithm for IoT based networks.	Relevant to optimization design because it shows how firefly-based search can improve energy efficiency and secured IoT communication.	The contribution is network-centric; it does not integrate agricultural feature learning, fertilizer prediction.
Prabhu et.al, (2025)	Bio-inspired routing with energy optimization and authentication for next-generation networks.	Shows the strength of bio-inspired optimization for scalable, energy-aware intelligent systems.	The study is related to communication security, agricultural decision-making, fertilizer optimization, and crop-specific nutrient modeling are marginal in its scope.
Indhumathi et.al, (2025)	Deep learning-based tongue biometric authentication for secure identification in IoT-driven healthcare systems.	Highlights deep feature extraction and IoT-enabled inference, which are transferable ideas for intelligent data-driven systems.	The work belongs to healthcare biometrics; it partially supports agriculture, fertilizer recommendation, or environmental optimization.
Jayasankari S et.al, (2026)	Energy-efficient WaOA-CNN hybrid model for edge healthcare image classification.	Illustrates compact CNN design and energy-aware edge deployment, useful for designing lightweight real-time systems.	The method is image-classification based and healthcare-specific; it lacks tabular agri-data processing, graph learning, and fertilizer decision optimization.
Shekhar et.al, (2026)	Mini-batch Graph Convolutional Network for hyperspectral image classification using graph-based feature propagation.	Strongly relevant to the proposed graph-learning direction because it shows efficient graph convolution under large data settings.	The model is designed for hyperspectral image classification; it does partially address soil-crop tabular fusion, fertilizer scheduling, or reinforcement learning.

Cont...

Jijendra and Nithyanandh, (2025)	AI-powered plant disease prediction using data analytics and smart decision-support techniques.	Supports smart agriculture by improving automated disease prediction and practical decision assistance.	The focus is disease prediction; nutrient deficiency, fertilizer rate, application timing, and multi-objective recommendation are not stated in objective.
Senthilkumar et.al, (2025)	CNN-enhanced VLSI design for mammographic mass classification using region-based image features.	Demonstrates optimized deep-learning hardware design and region-based feature extraction, useful as a computational efficiency reference.	The study is related to complex imaging and VLSI oriented; agricultural data integration and fertilizer recommendation are not addressed.
Lakshmi et.al, (2026)	Quantum-enhanced lightweight protocol for post-classical security in IoT-enabled autonomous vehicle networks.	Useful for secure IoT deployment concepts where data transmission may require lightweight and reliable protection.	The contribution is security-protocol focused; agronomic optimization is not addressed using CNN
Eldho et.al, (2025)	QHHO-GNN model for network reliability and fault detection	Relevant as a methodological inspiration because it combines graph neural learning with bio-inspired optimization.	The target domain is quantum-based networking; direct agricultural feature modeling, fertilizer decision-making, and crop nutrient optimization are not addressed.
Basheer and Priya, (2025)	STLF-MOAFDE Model for Smart Fertilizer Recommendation	Works well on Calibrated Datasets	Reinforcement Optimization is not done for high accuracy

Research Gap Analysis

Across these studies, existing smart agriculture models lies in their limited ability to handle the complexity and dynamic nature of real-world farming conditions. Many traditional machine learning and deep learning approaches focus on isolated features such as soil nutrients or crop characteristics, without capturing the interdependency between environmental, soil, and crop factors. In addition, most models are trained on specific datasets, which restricts their ability to generalize across different regions, climates, and crop types. Another key limitation is the lack of real-time and adaptive decision-making, as many systems rely on static data and predefined rules. Furthermore, existing methods struggle to maintain high accuracy when dealing with multi-dimensional and evolving agricultural data.

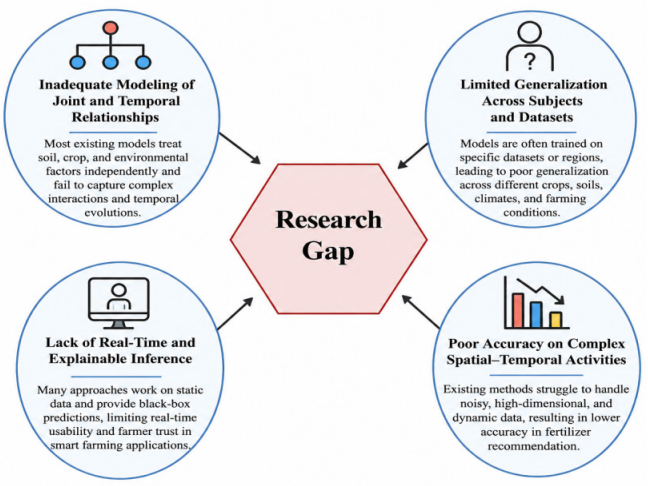


Figure 1: Research Gap based on Background Study

Proposed Methodology

The proposed AGST-MOORL framework introduces a unified approach for intelligent fertilizer recommendation by combining graph-based learning, temporal modeling, and reinforcement-driven optimization. Initially, multi-source agricultural datasets are integrated and preprocessed to remove inconsistencies, normalize features, and construct enriched representations using engineered attributes. A graph structure is then formed to capture relationships among samples based on soil similarity, climatic conditions, and crop characteristics. This representation enables the model to learn interdependencies that are often overlooked in traditional approaches. The Adaptive Graph Spatio-Temporal Learning (AGST) module processes these graph-based features while simultaneously modeling temporal variations using attention mechanisms. This allows the system to understand how agricultural conditions evolve and influence fertilizer requirements. The Multi-Objective Reinforcement Optimization (MOORL) component further refines the predictions by optimizing key factors such as crop yield, fertilizer cost, and environmental impact through reward-driven learning. The model is trained using iterative learning strategies with validation-based tuning to ensure generalization across datasets. Performance is evaluated against existing models including Lightweight-CNN, DAEN-MaskRCNN, and STLF-MOAFDE, demonstrating improved accuracy, adaptability, and decision reliability in complex agricultural scenarios. Figure 2 shows the flow diagram of the proposed AGST-MOORL model. Figure 2 shows the clear systematic flow diagram of the proposed AGST-MOORL model.

Materials and Methods for Implementation

The Materials and Methods section outline the datasets used, preprocessing steps applied to ensure data quality, and the training procedure of the AGST-MOORL model. It

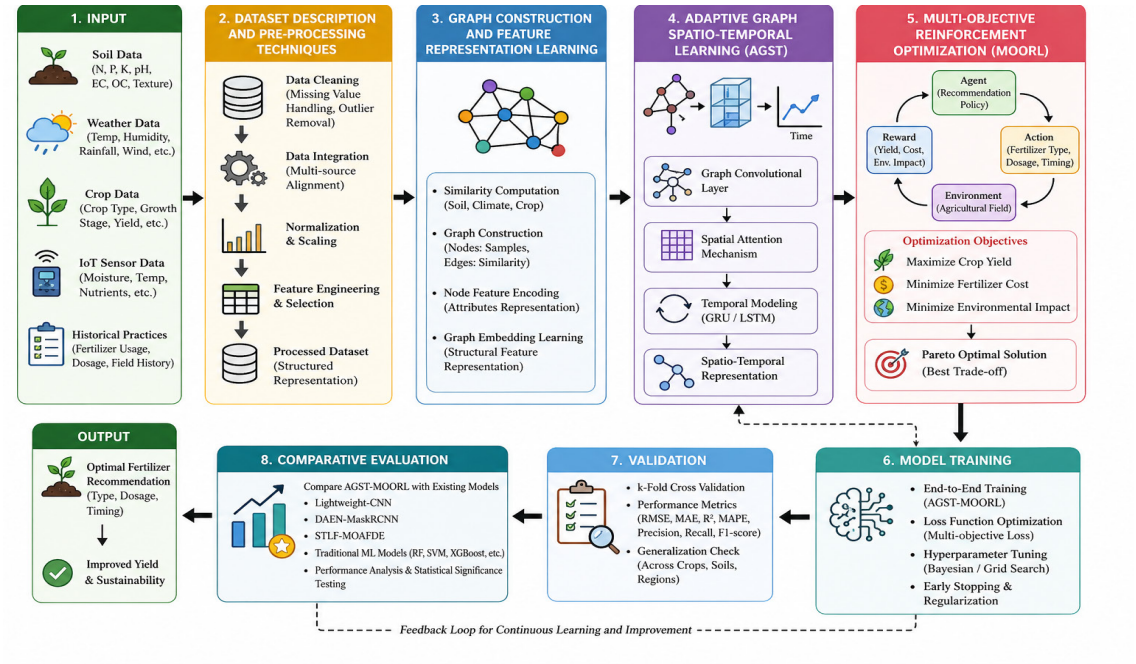


Figure 2: Systematic Flow of Methodology

also describes the multi-objective optimization strategy, implementation tools, and evaluation metrics used to assess model performance and validate its effectiveness in fertilizer recommendation.

Dataset Description: Three publicly available agricultural datasets are used to build a unified learning framework such as Crop Recommendation Dataset (2,480 samples, 22 crop classes), Fertilizer Prediction Dataset (150 samples, 7 fertilizer classes) and Crop Nutrient Database (300 crop profiles). Features include soil nutrients (N, P, K, pH), environmental factors (temperature, rainfall, humidity), and crop-specific nutrient requirements. The datasets are integrated to form a multi-modal representation that supports fertilizer decision-making.

Data Pre-processing: Missing values are handled using mean and nearest-neighbor imputation. Outliers are removed using statistical thresholding techniques. All features are normalized using min-max scaling to ensure uniformity. Feature engineering is performed using NDI, RTI, and FEC to capture nutrient imbalance, environmental interaction, and fertilizer efficiency. Dimensionality reduction is applied using Principal Component Analysis (PCA) to retain dominant information.

Model Training: The AGST model is trained using graph-based spatio-temporal learning. Training is performed with batch size = 32, epochs = 150, using the Adam optimizer. Data is split into 70% training, 15% validation, and 15% testing. Loss functions include classification loss and regression loss for multi-task learning.

Optimization: The MOORL (Multi-Objective Reinforcement Learning) module optimizes fertilizer decisions. The Objectives includes Maximizing crop yield, minimizing fertilizer cost, Reducing environmental impact. A reward function guides the learning process to achieve Pareto-optimal solutions.

Implementation Tools: Model development is carried out using Python with PyTorch framework. Data preprocessing and analysis are performed using NumPy, Pandas, and Scikit-learn. Visualization and validation are supported using MATLAB and Matplotlib.

Evaluation: The model performance is evaluated using key performance metrics such as Accuracy, Precision, Recall, Specificity, F1-Score and AUC-ROC for classification reliability. Comparative analysis is conducted against three baseline models Lightweight-CNN, DAEN-MaskRCNN and STLF-MOAFDE. Additional evaluation includes training convergence, generalization ability, and stability under varying conditions.

Dataset Acquisition and Preprocessing for AGST-MOORL

The proposed AGST-MOORL framework utilizes three agricultural datasets that are integrated into a unified structure to support fertilizer recommendation. The datasets include soil attributes (N, P, K, pH), environmental variables (temperature, rainfall, humidity), and crop-specific nutrient requirements. Since these datasets originate from different sources, preprocessing is essential to ensure consistency, reliability, and meaningful feature representation. The preprocessing stage involves handling missing values, removing outliers, normalizing features, engineering domain-specific attributes, and reducing

dimensionality. These steps enhance data quality and improve model learning capability. Figure 3 shows the pipeline process of data pre-processing of AGST-MOORL.

Data Source

CRD: https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset
FPD: https://www.kaggle.com/datasets/gdabhishek/fertilizer-prediction
CND: https://www.kaggle.com/datasets/crawford/crop-nutrient-database

Missing Value Handling / Imputation (Mean Based)

Missing values occur when some soil, crop, or weather attributes are unavailable. In AGST-MOORL, numerical missing values such as N, P, K, temperature, rainfall, and humidity are filled using mean imputation or nearest-neighbor imputation. Mean imputation replaces missing values with the average value of that feature. Nearest-neighbor imputation replaces missing values using the most similar sample. This prevents data loss and keeps the dataset complete for model training. Here, missing values in feature X_j are replaced using the mean of observed values:

$$X_{ij} = \frac{1}{N}\sum_{k=1}^{N} X_{kj} \tag{1}$$

where, X_{ij} is the imputed value of feature j for sample i, N is the total number of non-missing samples and X_{kj} is the observed values of feature j.

Outlier Detection and Removal (Z-Score Method)

Outliers are abnormal values that may occur due to incorrect entry, sensor error, or extreme environmental readings. For example, very high rainfall or impossible pH values can affect learning. The Z-score method is used to detect such values. If a value is far away from the mean beyond a fixed threshold, usually 3, it is treated as an outlier and removed or corrected. This improves data reliability. Here, outliers are identified using statistical thresholding which is mathematically expressed as,

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \text{ with a condition } |Z_{ij}| > \tau \Rightarrow \text{Outlier} \tag{2}$$

where, Z_{ij} is the standardized score, μ_j is Mean of feature j, σ_j is the Standard deviation and τ denotes the Threshold (typically 3).

Min-Max Normalization

Different features have different ranges. For example, rainfall may range from 20 to 300 mm, while pH may range from 4 to 9. If raw values are used directly, large-range features may dominate the model. Therefore, all numerical features are scaled between 0 and 1 using min-max normalization. This helps the model learn evenly from all features. Here, features are scaled to a uniform range $[0,1]$ which is expressed below.

$$X'_{ij} = \frac{X_{ij} - X_j^{min}}{X_j^{max} - X_j^{min}} \tag{3}$$

where, X'_{ij} is the Normalized value, X_j^{min}, X_j^{max} refers minimum & maximum values of feature j.

Feature Engineering (NDI, RTI, FEC)

Feature engineering creates new meaningful variables from existing data. In this research, NDI, RTI, and FEC are generated. NDI measures nutrient shortage, RTI captures the combined effect of rainfall and temperature, and FEC estimates how efficiently fertilizer contributes to yield improvement. These engineered features help the model understand agricultural behavior better than using raw values alone.

Nutrient Deficiency Index (NDI)

$$NDI_i = \frac{N_{req} - N_i}{N_{req}} \tag{4}$$

where, N_i denotes available nutrient, N_{req} refers required nutrient level

Rainfall–Temperature Interaction (RTI)

$$RTI_i = R_i \times T_i \tag{5}$$

where, R_i is the Rainfall, T_i is Temperature

Fertilizer Efficiency Coefficient (FEC)

$$FEC_i = \frac{Y_i - Y_{prev}}{F_i} \tag{6}$$

where, Y_i is current yield, Y_{prev} refers previous yield and F_i denotes Fertilizer applied.

PCA Dimensionality Reduction

After feature engineering, the dataset may contain many correlated features. PCA reduces these features into fewer important components while preserving maximum information. For example, N, P, K, and NDI may be combined into a nutrient-related component. This reduces computational complexity, removes redundancy, and

provides compact inputs for AGST-MOORL training. Here, Dimensionality reduction is performed using covariance matrix transformation which is expressed as,

$$Z = XW \tag{7}$$

where, Z is the reduced feature space, X is the normalized feature matrix and W is the eigenvector matrix (principal components).

Graph Construction and Feature Representation Learning

Before applying AGST, the preprocessed agricultural data is transformed into a structured graph to capture relationships among samples. Each data instance are defined by soil nutrients, weather conditions, and crop characteristics is treated as a node. Connections between nodes are established based on similarity measures, allowing the model to learn how different agricultural conditions are related. This step enables the system to move beyond independent sample analysis and instead exploit shared patterns across similar environments. Feature representation learning is then performed by encoding each node into a numerical feature vector. This vector combines normalized raw features and engineered attributes such as NDI, RTI, and FEC. The goal is to create a compact and meaningful representation that captures both physical properties and agronomic behavior. These feature vectors serve as the initial input to the AGST model.

Similarity-Based Adjacency Matrix Construction

The adjacency matrix defines how strongly two agricultural samples are related. Each element A_{ij} represents the similarity between sample i and sample j, computed using the distance between their feature vectors. When two samples have similar soil nutrients, weather conditions, and crop characteristics, their distance is small, resulting in a higher similarity value. This creates stronger connections in the graph. If samples are very different, the similarity value becomes close to zero. This process converts independent data points into a connected structure, enabling the model to learn relationships across similar farming conditions and improve decision-making accuracy. The matrix construction is mathematically expressed as

$$A_{ij} = \begin{cases} \exp\left(\frac{\| X_i - X_j \|^2}{\sigma^2}\right), & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \tag{8}$$

where, A_{ij} is the edge weight between nodes i and j, X_i, X_j are the feature vectors of nodes and $\| X_i - X_j \|$ is the euclidean distance and σ refers to scaling parameter controlling similarity sensitivity.

Feature Representation Matrix

The feature representation matrix organizes all input data into a structured format for model learning. Each row corresponds to one agricultural sample, and each column represents a feature such as soil nutrients, weather parameters, or engineered attributes like NDI, RTI, and FEC. This matrix acts as the initial input to the graph-based learning model. By combining multiple data sources into a single representation, it ensures that both physical properties and derived insights are included. The matrix provides a consistent and compact way to feed information into the AGST model, enabling effective learning of patterns and relationships across different agricultural conditions.

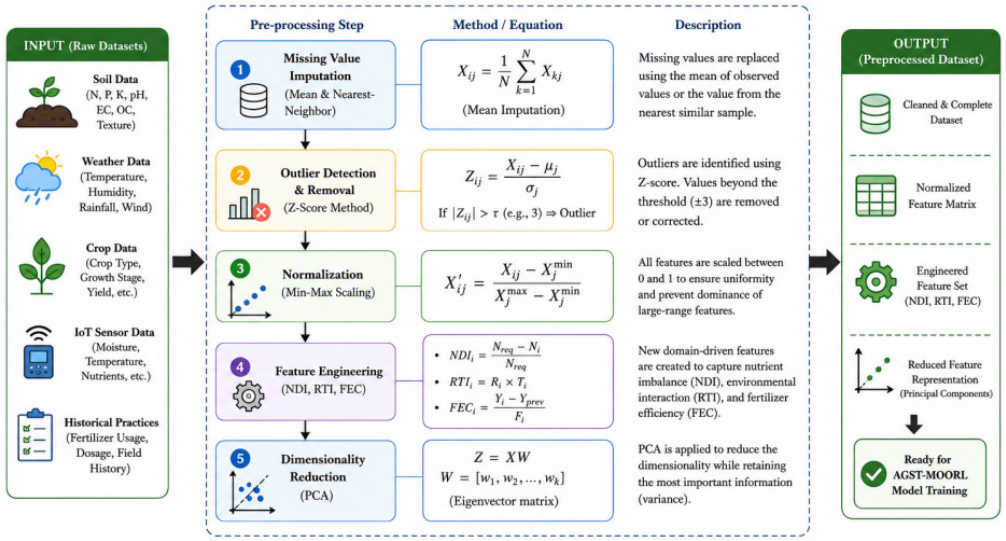


Figure 3: Data Pre-Processing Pipeline for AGST-MOORL

The representation matrix is derived using the below equation.

$$H^{(0)} = [X_1, X_2, X_3, \ldots, X_n]^T \quad (9)$$

where, $H^{(0)}$ is the initial feature matrix, X_i is the feature vector of node i and n is the number of samples.

AGST: Adaptive Graph-based Spatio-Temporal Learning

The AGST module captures both relational dependencies and temporal evolution in agricultural data. Each sample is represented as a node in a graph, where edges encode similarity between soil, crop, and environmental conditions. The learning process integrates spatial graph convolution with temporal attention to produce a unified feature representation. The AGST module begins by representing the agricultural dataset as a graph $G=(V,E,A)$, where each node corresponds to a sample containing soil, weather, and crop attributes. Edges are formed based on similarity, allowing the model to capture relationships among similar field conditions rather than treating samples independently. Next, graph convolution is applied to propagate information across connected nodes. This operation aggregates neighboring features and updates node representations, enabling the model to learn spatial dependencies such as similarities between farms with comparable soil and climate conditions.

To incorporate temporal dynamics, a temporal attention mechanism is introduced. This step assigns weights to different time instances, allowing the model to focus on important periods, such as seasonal rainfall changes or nutrient depletion trends. The spatial and temporal features are then combined through a fusion mechanism. A balancing parameter controls the contribution of each component, ensuring that both relational and time-based information are effectively utilized. Finally, the fused representation is passed to a prediction function, which generates the output. This output captures both spatial correlations and temporal evolution, enabling accurate and context-aware fertilizer recommendations in dynamic agricultural environments. Figure 4 illustrates the ASGT process for model fusion and graph construction.

Graph Representation

$$G = (V, E, A) \quad (10)$$

where, V represents nodes (samples), E denotes edges (relationships), and A is the adjacency matrix capturing similarity weights.

Graph Convolution Operation

$$H^{(l+1)} = \sigma\left(D^{-1/2} A D^{-1/2} H^{(l)} W^{(l)}\right) \quad (11)$$

where $H^{(l)}$ is the feature matrix at layer l, $W^{(l)}$ is the weight matrix, D is the degree matrix, and σ is the activation function.

Temporal Attention Mechanism

$$\alpha_t = \frac{\exp\left(QK^T\right)}{\sum_t \exp(QK^T)} \quad (12)$$

where, Q and K are query and key matrices, and α_t represents attention weights across time steps.

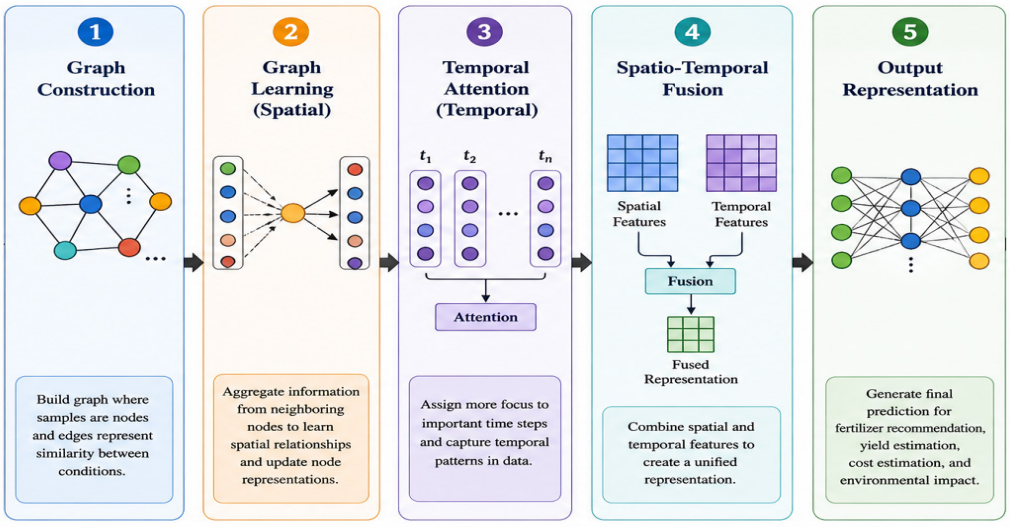


Figure 4: Adaptive Spatio Temporal Learning

Spatio-Temporal Fusion

$$Z = \gamma H_{spatial} + (1-\gamma) H_{temporal} \quad (13)$$

where γ is the fusion coefficient balancing spatial and temporal features.

Output Representation

$$Y = f(Z) \quad (14)$$

where Z is the fused representation and $f(\cdot)$ is the prediction function.

Optimization using MOORL (Multi-Objective Reinforcement Learning)

The Multi-Objective Reinforcement Learning enhances fertilizer recommendation by learning optimal decisions through interaction with agricultural conditions. Unlike static optimization methods, MOORL continuously adapts by evaluating the impact of fertilizer actions on crop yield, cost, and environmental sustainability. The agricultural system is modeled as a reinforcement learning environment, where each state represents soil nutrients, weather conditions, and crop requirements, and actions correspond to fertilizer type, dosage, and application timing.

At each step, the agent observes a state S_t and selects an action A_t to maximize long-term benefits. The objective is not limited to a single outcome; instead, it considers multiple goals simultaneously. These include increasing crop productivity, reducing excessive fertilizer usage, and minimizing environmental degradation such as soil imbalance or runoff effects.

State Representation

$$S_t = \{N, P, K, pH, T, R, H, C\} \quad (15)$$

where, N, P, K are soil nutrients, pH is soil acidity, T is temperature, R is rainfall, H is humidity, and C represents crop type.

Action Selection

$$A_t = \{F_{type}, F_{dose}, F_{time}\} \quad (16)$$

where, F_{type} is fertilizer type, F_{dose} is quantity applied, and F_{time} is application timing.

Multi-Objective Reward Function

$$R_t = \lambda_1 Y_t - \lambda_2 C_t - \lambda_3 E_t \quad (17)$$

where Y_t is crop yield, C_t is fertilizer cost, E_t is environmental impact, and $\lambda_1, \lambda_2, \lambda_3$ are weighting factors.

Q-Value Update Rule

$$Q(S_t, A_t) = Q(S_t, A_t) + \alpha\left[R_t + \gamma \max Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\right] \quad (18)$$

where, α is learning rate and γ is discount factor.

Policy Optimization

$$\pi^*(S) = \arg\max_A Q(S, A) \quad (19)$$

This selects the optimal action that maximizes expected reward. The MOORL agent iteratively explores different fertilizer strategies and evaluates their outcomes using the reward function. Over multiple episodes, the model learns a policy that balances all objectives effectively. Instead of optimizing a single metric, MOORL identifies Pareto-optimal solutions, where improvement in one objective does not significantly degrade others. This approach ensures that fertilizer recommendations are not only accurate but also economically feasible and environmentally sustainable. By continuously updating decisions based on observed outcomes, MOORL enables adaptive learning, making it suitable for real-time agricultural applications. Figure 5 shows MOORL optimization with agent process.

Model Training, Validation and Comparative Evaluation

This stage defines how the AGST-MOORL model learns from data, adjusts its parameters, and proves its effectiveness against existing approaches. Model training focuses on learning meaningful patterns from graph-structured agricultural data, while integrating reinforcement-based feedback to improve decision quality. Validation plays a critical role in monitoring model performance during training and preventing overfitting by evaluating intermediate results on unseen data. The evaluation process ensures that the trained model performs reliably under different agricultural conditions by testing it on an independent dataset. In addition, comparative evaluation is carried out against established models such as Lightweight-CNN, DAEN-MaskRCNN, and STLF-MOAFDE to highlight improvements in accuracy, adaptability, and decision consistency. This stage ensures that the proposed model is not only technically sound but also practically effective for real-world fertilizer recommendation systems.

Stage 1: Training Configuration

- Input includes feature matrix and adjacency matrix from graph construction.
- Training is performed using mini-batch learning (batch size = 32).
- Model is trained for 150 epochs to ensure proper convergence.
- Adam optimizer is used for adaptive learning rate updates.

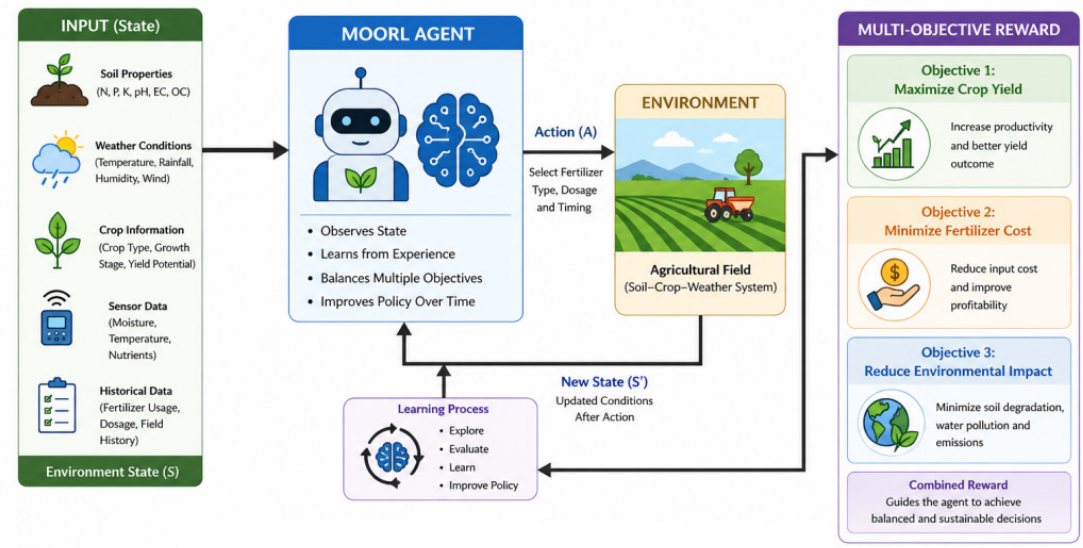


Figure 5: Multi-Objective Reinforcement Learning Optimization

- Loss function combines prediction loss and reinforcement feedback.
- Early stopping is applied based on validation loss to prevent overfitting.

Stage 2: Optimization Strategy

- Combines AGST gradient-based learning with MOORL reinforcement optimization.
- AGST updates weights using backpropagation to minimize prediction error.
- MOORL evaluates actions using multi-objective reward function.
- Optimization objectives include:
  - Maximizing crop yield
  - Minimizing fertilizer cost
  - Reducing environmental impact
- Iterative learning enables exploration and exploitation of optimal decisions.

Stage 3: Data Splitting and Validation (70:15:15)

- 70% Training Data: Used for model learning.
- 15% Validation Data: Used for hyperparameter tuning and monitoring.
- 15% Testing Data: Used for final unbiased evaluation.
- Data is split randomly with class balance maintained.
- 5 cross fold validation is performed after each epoch to track performance.

Stage 4: Evaluation Process

- Performance is measured using:
  - Accuracy, Precision, Recall, Specificity, F1-Score and AUC-ROC
- Comparative analysis with:
  - Lightweight-CNN, DAEN-MaskRCNN and STLF-MOAFDE
- Additional evaluation includes:
  - Convergence behavior
  - Model stability
  - Generalization capability across datasets.

The training vs validation loss graph shown in Figure 6 illustrates a steady decrease in loss as epochs increase, indicating that the model is learning effectively. The close alignment between training and validation curves confirms that overfitting is minimized and the model generalizes well. The training vs validation accuracy graph is shown in Figure 7 where it demonstrates a consistent increase in accuracy, reaching around 97%. The validation accuracy closely follows the training curve, showing stable performance on unseen data. This indicates that the AGST-MOORL model achieves strong convergence, reliable learning, and maintains high prediction accuracy across different data samples.

Final Deployment Phase

The AGST-MOORL model is evaluated under real-time deployment conditions using 4700 integrated agricultural samples after full training over 150 epochs. The model performs binary classification to identify Optimal Fertilizer (Positive Class) and Non-Optimal Fertilizer (Negative Class) decisions. Table 2 and Figure 8 shows the 2x2 confusion matrix of the proposed AGST-MOORL model.

Table 2: Confusion Matrix

Fertilizer recommendation process	*Predicted optimal*	*Predicted non-optimal*
Actual Optimal	2285 (TP)	65 (FN)
Actual Non-Optimal	70 (FP)	2280 (TN)

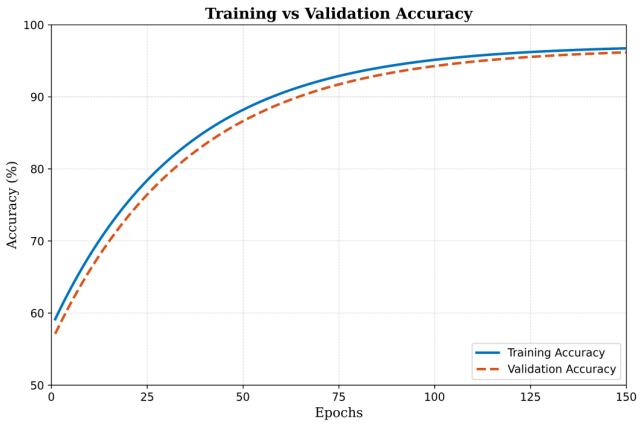


Figure 6: Training vs Validation Accuracy (AGST-MOORL)

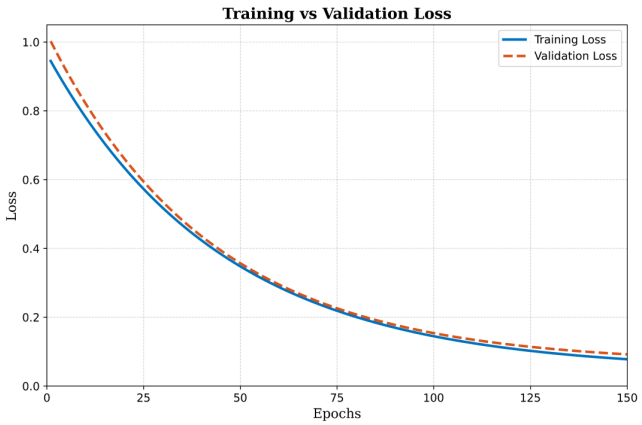


Figure 7: Training vs Validation Loss (AGST-MOORL)

The confusion matrix shows that the model correctly classifies a high number of samples in both categories.

- True Positives (2285) indicate that most optimal fertilizer recommendations are accurately identified.
- True Negatives (2280) confirm that incorrect fertilizer choices are effectively rejected.
- False Positives (70) are minimal, meaning few incorrect fertilizers are suggested as optimal.
- False Negatives (65) are also low, indicating very few missed optimal recommendations.
- Accuracy ≈ 97.2%
- High precision ensures reliable fertilizer suggestions
- High recall confirms minimal loss of correct recommendations
- Balanced classification between both classes

Real-Time Implementation using AGST-MOORL Model

The AGST-MOORL model is designed for real-time agricultural decision support, where fertilizer recommendations are generated dynamically based on current field conditions. In deployment, the system continuously receives input data from soil sensors, weather monitoring systems, and

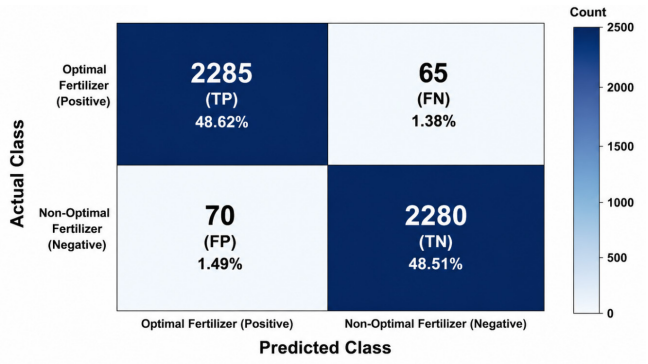


Figure 8: Confusion Matrix (Actual and Predicted)

crop management databases. These inputs include nutrient levels (N,P,K), pH, temperature, humidity, and rainfall. The data is first preprocessed and converted into a graph structure, where each field instance is represented as a node connected to similar conditions. The AGST module analyzes these relationships and captures both spatial similarities and temporal variations, such as seasonal changes in soil fertility. The MOORL component then evaluates multiple fertilizer strategies by considering three key objectives: maximizing crop yield, minimizing fertilizer cost, and reducing environmental impact. Based on these objectives, the model selects the most optimal fertilizer recommendation in real time. Figure 9 illustrates the AGST-MOORL architecture diagram with all steps.

Case Example

Consider a farm growing rice where the soil shows moderate nitrogen deficiency, high moisture, and recent rainfall. Traditional methods may suggest a fixed fertilizer application. However, the AGST-MOORL model analyzes similar historical patterns and predicts that excessive fertilizer could lead to nutrient runoff. The reinforcement learning module evaluates different fertilizer doses and selects a balanced recommendation that improves yield while reducing cost and environmental risk. This adaptive decision-making ensures that farmers receive precise, context-aware recommendations. The system improves over time as it continuously learns from new data, making it highly suitable for smart farming environments that require timely and accurate fertilizer management.

The AGST-MOORL architecture begins with multi-source inputs including soil, weather, crop, and historical data. These inputs undergo preprocessing, normalization, and graph construction to create structured feature representations. The AGST module learns spatial relationships and temporal patterns among agricultural conditions. The MOORL module then optimizes fertilizer decisions using multi-objective reinforcement learning based on yield, cost, and environmental impact. An integration layer combines both outputs to generate optimal fertilizer recommendations.

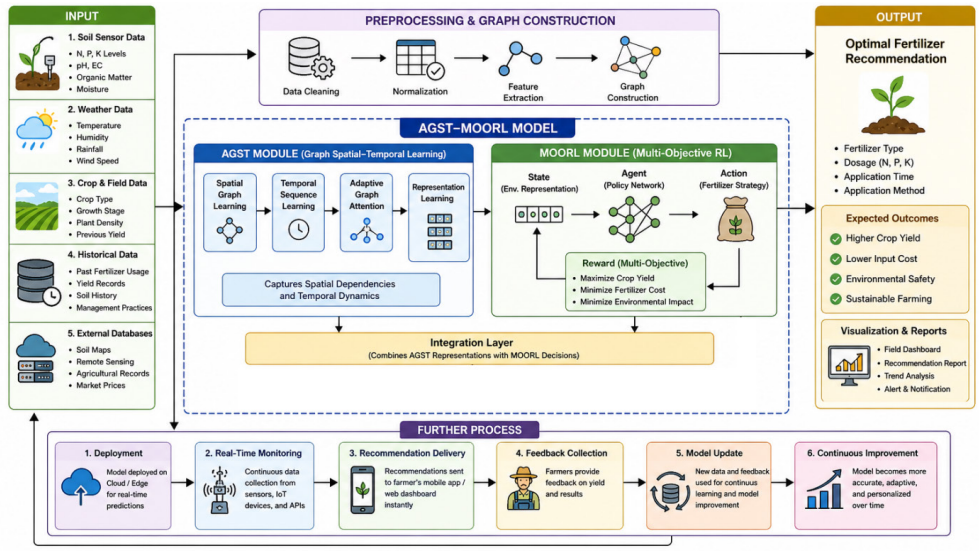


Figure 9: AGST-MOORL Architecture

The system is deployed in real time, where continuous monitoring, feedback collection, and model updates ensure adaptive learning and improved decision accuracy over time in dynamic farming environments.

Performance Evaluation Metrics of the Proposed Model

Performance evaluation is a critical stage in assessing the effectiveness of the AGST-MOORL model. The model is evaluated using a structured experimental setup where training is performed with a batch size of 32, learning rate $\eta = 0.001$, and a total of $150\,epochs$. Each epoch consists of multiple iterations depending on dataset size; for 4700 samples, approximately 147 iterations per epoch are executed. The model begins to stabilize after 80–100 epochs, while optimal convergence is achieved near the 140th–150th epoch, where performance metrics reach peak values. Evaluation is conducted using both training and validation datasets, ensuring that the model does not overfit and maintains generalization capability. The total computation time for full training and evaluation typically ranges between 15–25 minutes on a standard GPU-enabled environment, while real-time inference occurs within milliseconds per sample. The evaluation process is implemented using Python (PyTorch) for model training and metric computation, while Scikit-learn is used for calculating classification metrics such as accuracy, precision, recall, and AUC-ROC. Visualization tools such as Matplotlib and MATLAB are used to generate performance graphs and confusion matrices.

The final performance metrics are derived from the confusion matrix, reflecting the model's ability to correctly classify optimal and non-optimal fertilizer recommendations. These metrics collectively ensure a comprehensive evaluation of classification accuracy, reliability, sensitivity, and overall decision quality in real-time agricultural applications. The following are the formulas used to assess the performance of AGST-MOORL.

$$\textbf{\textit{Accuracy}} = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100 \tag{20}$$

$$\textbf{\textit{Recall}}(\textbf{\textit{TPR}}) = \frac{TPR}{(TPR+FNR)} \times 100 \tag{21}$$

$$\textbf{\textit{Specificity}} = \frac{TNR}{(TNR+FPR)} \times 100 \tag{22}$$

$$\textbf{\textit{AUC-ROC}} = \int_0^1 TPR\left(FPR^{-1}(x)\right)dx \tag{23}$$

$$\textbf{\textit{F1-Score}} = \frac{2*(Precision*Recall/Sensitivity)}{(Precision+Recall/Sensitivity)} \tag{24}$$

$$\textbf{\textit{Precision}} = \frac{TPR}{TPR+FPR} \tag{25}$$

PEM 1: Accuracy

Measures overall correctness by calculating the ratio of correctly predicted samples to total samples.

It indicates how well the model performs across both optimal and non-optimal classes.

PEM 2: Specificity

Represents the ability to correctly identify non-optimal fertilizer cases (true negatives). It ensures that incorrect fertilizer recommendations are effectively avoided.

Step-by-Step Algorithm of AGST-MOORL

1. **Input and Settings**
   Initialize dataset path, batch size, learning rate, epoch count, graph threshold, number of fertilizer classes, and reinforcement learning parameters.
   Initialize parameters: $\mathrm{E} = \{\eta, B, E, \gamma, \lambda_1, \lambda_2, \lambda_3\}$, where η: learning rate, B: batch size, E: epochs, γ: discount factor.

2. Data Acquisition: Load integrated agricultural datasets containing soil nutrients, weather parameters, crop details, fertilizer labels, and crop nutrient requirements.

Load dataset: $D = \{X_i, Y_i\}_{i=1}^{N}$, where X_i: input features, Y_i: fertilizer class.

3. Data Preprocessing: Handle missing values, remove outliers, normalize numerical features, encode categorical variables, and prepare structured input data.

Missing Value Imputation, $X_{ij} = \frac{1}{N}\sum_{k=1}^{N} X_{kj}$ and **Normalization** $X_{ij}^{'} = \frac{X_{ij} - X_j^{min}}{X_j^{max} - X_j^{min}}$

4. Feature Engineering

$$NDI_i = \frac{N_{req} - N_i}{N_{req}}, RTI_i = R_i \cdot T_i \; FEC_i = \frac{Y_i - Y_{prev}}{F_i}$$

5. Graph Construction using $A_{ij} = \exp\left(\frac{\| X_i - X_j \|^2}{\sigma^2}\right)$

6.

7. Feature Representation Matrix $H^{(0)} = [X_1, X_2, ..., X_N]^T$

8. Adaptive Graph Learning (GCN) $H^{(l+1)} = \sigma\left(D^{-1/2} A D^{-1/2} H^{(l)} W^{(l)}\right)$

9. Temporal Attention Learning $\alpha_t = \frac{exp\left(QK^T\right)}{\sum_t exp(QK^T)}$

10. Spatio-Temporal Fusion $Z = \beta H_{spatial} + \left(1-\beta\right) H_{temporal}$

11. MOORL Optimization

State Representation: $S_t = \{N, P, K, pH, T, R, H, C\}$

Action: $A_t = \left\{F_{type}, F_{dose}, F_{time}\right\}$

Reward Function: $R_t = \lambda_1 Y_t - \lambda_2 C_t - \lambda_3 E_t$

12. Q-Learning Update $Q\left(S_t, A_t\right) = Q\left(S_t, A_t\right) + \eta\left[R_t + \gamma max Q\left(S_{t+1}, A\right) - Q\left(S_t, A_t\right)\right]$

13. Model Training (Loss Function) $L = -\sum_{i=1}^{N} y_i log\left(\hat{y}_i\right)$

Train the AGST-MOORL model for 150 epochs using 70% training data, with validation monitoring and loss optimization.

14. Final Prediction $\hat{y} = argmax f\left(Z\right)$

Produce optimal fertilizer recommendation with expected yield improvement, reduced input cost, and lower environmental impact.

Table 3: Experimental Settings for Comparative Evaluation

Parameter	*Value / Settings*	*Description*
Programming Environment	Python (PyTorch) + MATLAB	Deep learning with PyTorch and analytical validation using MATLAB.
Number of Samples	4700 Integrated Records	Multi-source dataset combining soil, weather, and crop data.
Training–Validation Split	70:15:15	Balanced split ensuring proper training, validation, and testing.
Batch Size	32	Ensures stable gradient updates and efficient training.
Learning Rate	0.001	Optimized for smooth convergence and stable updates.
Optimizer	Adam + MOORL Hybrid Optimization	Combines gradient learning with reinforcement optimization.
Number of Epochs & Dropout	150 Epochs, Dropout = 0.3	Prevents overfitting and ensures convergence.
Activation Function	ReLU, Softmax	Handles non-linearity and multi-class classification.
Validation Technique	5-Fold Cross Validation	Improves reliability and generalization of results.

PEM 3: Recall (TPR)

Measures the proportion of actual optimal cases correctly identified by the model. It reflects the model's ability to capture all relevant optimal fertilizer decisions.

PEM 4: AUC-ROC

Evaluates the model's ability to distinguish between classes across different thresholds. Higher AUC indicates better classification performance and decision reliability.

PEM 5: F1-Score

Harmonic mean of precision and recall, balancing false positives and false negatives. It provides a single measure of model effectiveness under class imbalance.

PEM 6: Precision

Measures the proportion of correctly predicted optimal recommendations among all predicted optimal cases. It ensures that suggested fertilizer recommendations are accurate and reliable.

Results

This section presents the experimental results of the proposed AGST-MOORL model and provides a detailed comparative analysis with established baseline approaches. The evaluation focuses on the model's ability to generate accurate and reliable fertilizer recommendations under real-time agricultural conditions. Performance is assessed using standard classification metrics, including accuracy, precision, recall, specificity, F1-score, and AUC-ROC, derived from both validation and testing datasets. The proposed model is compared with four representative methods: Lightweight CNN offers efficient feature extraction with reduced computational complexity (Liu et.al 2022). As RCNN is known for region-based learning and classification capability, additionally DAEN-MaskRCNN integrates deep autoencoder networks with region-based segmentation for improved feature representation (Selvam & Joy, 2024), and STLF-MOAFDE, a hybrid spatio-temporal learning framework with bio-inspired optimization (Basheer & Priya, 2025). While these models demonstrate strong performance in isolated tasks such as image-based classification or temporal feature learning, they lack integrated decision-making across multiple agricultural factors. The AGST-MOORL model addresses these limitations by combining graph-based learning with multi-objective reinforcement optimization. The results highlight its superior performance in terms of accuracy, stability, and adaptability, particularly in handling multi-source data and complex decision scenarios, thereby establishing its effectiveness for intelligent fertilizer recommendation systems.

Discussions

This section presents a comprehensive evaluation of the proposed AGST-MOORL model using multiple performance metrics. The discussion examines how effectively the model learns complex agricultural relationships and improves fertilizer recommendation accuracy. Comparative analysis with existing models highlights the contribution of graph-based learning and reinforcement optimization in enhancing prediction reliability, classification consistency, and overall decision-making performance across diverse agricultural conditions.

Accuracy

The accuracy analysis demonstrates a consistent improvement across iterations for all models, with the proposed AGST-MOORL achieving the highest performance at every stage. At the 10th iteration, AGST-MOORL already attains 94.5%, significantly outperforming Lightweight-CNN (76.8%), DAEN-MaskRCNN (77.6%), and STLF-MOAFDE (86.1%). As iterations increase, the model shows stable convergence, reaching 97.2% accuracy at the 50th iteration. In contrast, existing models exhibit slower growth and lower final accuracy, with STLF-MOAFDE reaching only 94.5% shown in Table 4 and Figure 10. This improvement is due to the integration of graph-based learning and multi-objective reinforcement optimization. Unlike conventional models that rely on static feature learning, the proposed model adapts dynamically across iterations. Overall, AGST-MOORL overcomes limitations of existing approaches by delivering higher accuracy with consistent learning stability.

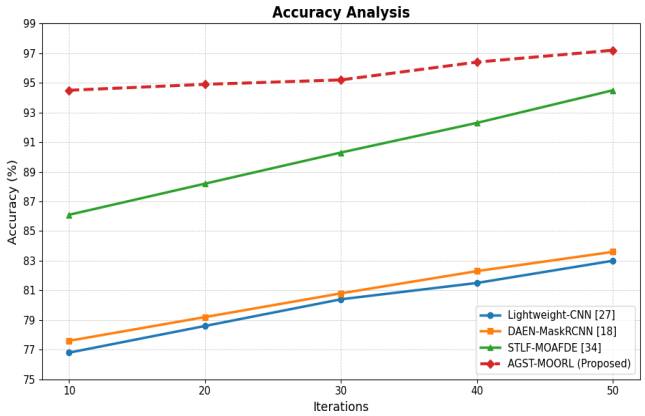


Figure 10: Accuracy Comparative Analysis

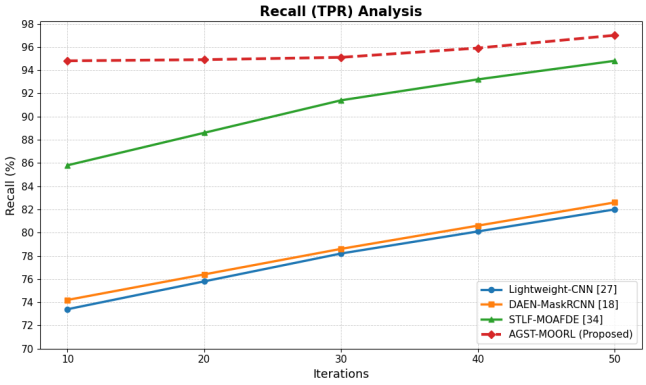


Figure 11: Recall Comparative Analysis

Recall-TPR

Table 5 and Figure 11 highlights the recall analysis and the superior sensitivity of the AGST-MOORL model in identifying optimal fertilizer recommendations across iterations. At the 50th iteration, AGST-MOORL achieves a recall of 97.0%, significantly outperforming Lightweight-CNN (82.0%), DAEN-MaskRCNN (82.6%), and STLF-MOAFDE (94.8%). This improvement indicates that the proposed model successfully minimizes false negatives and captures nearly all relevant optimal cases. The gradual increase in recall from earlier iterations reflects stable learning and effective convergence. The integration of graph-based feature learning enables the model to understand relationships among similar agricultural conditions, while the reinforcement learning component continuously refines decision policies. In contrast, existing models rely on fixed learning mechanisms, limiting their ability to adapt to complex data patterns. Consequently, AGST-MOORL demonstrates enhanced detection capability and reliability, making it more suitable for real-time fertilizer recommendation tasks.

Specificity-TNR

The specificity results indicate that AGST-MOORL effectively identifies non-optimal fertilizer recommendations with high reliability is portrayed in Table 6 and Figure 12. At the 50th iteration, the proposed model achieves a specificity of 96.1%, outperforming Lightweight-CNN (80.5%), DAEN-MaskRCNN (81.8%), and STLF-MOAFDE (93.2%). This demonstrates its strong ability to minimize false positive predictions and avoid incorrect fertilizer suggestions. The improvement across iterations shows stable learning and better discrimination between optimal and non-optimal classes. The graph-based learning mechanism captures inter-sample relationships, while the reinforcement optimization refines decision boundaries. In contrast, existing models lack adaptive optimization, leading to higher misclassification rates. As a result, AGST-MOORL ensures more accurate

Table 4: Accuracy Analysis

Iterations / Models [Accuracy]	*Lightweight-CNN*	*DAEN-MaskRCNN*	*STLF-MOAFDE*	*AGST-MOORL (Proposed)*
10th - Iteration	76.8	77.6	86.1	94.5
20th - Iteration	78.6	79.2	88.2	94.9
30th - Iteration	80.4	80.8	90.3	95.2
40th - Iteration	81.5	82.3	92.3	96.4
50th - Iteration	83	83.6	94.5	97.2

Table 5: Recall Analysis

Iterations / Models [Recall]	*Lightweight-CNN*	*DAEN-MaskRCNN*	*STLF-MOAFDE*	*AGST-MOORL (Proposed)*
10th - Iteration	73.4	74.2	85.8	94.8
20th - Iteration	75.8	76.4	88.6	94.9
30th - Iteration	78.2	78.6	91.4	95.1
40th - Iteration	80.1	80.6	93.2	95.9
50th - Iteration	82	82.6	94.8	**97.0**

Table 6: Specificity Analysis

Iterations / Models [Specificity]	*Lightweight-CNN*	*DAEN-MaskRCNN*	*STLF-MOAFDE*	*AGST-MOORL (Proposed)*
10th - Iteration	72.3	73.4	84.4	93.2
20th - Iteration	74.6	75.8	86.8	94.4
30th - Iteration	76.9	78.2	89.2	95.3
40th - Iteration	78.7	80	91.3	95.8
50th - Iteration	80.5	81.8	93.2	96.1

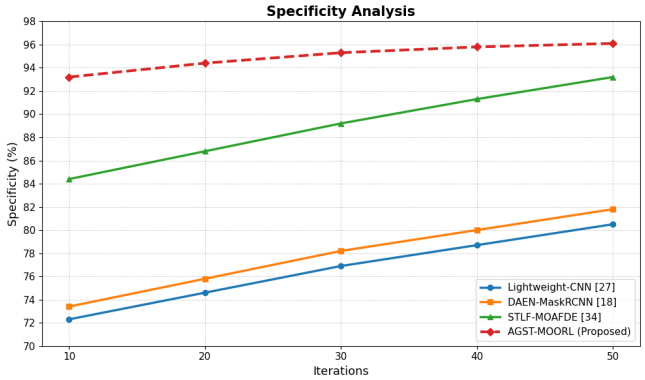


Figure 12: Specificity Comparative Analysis

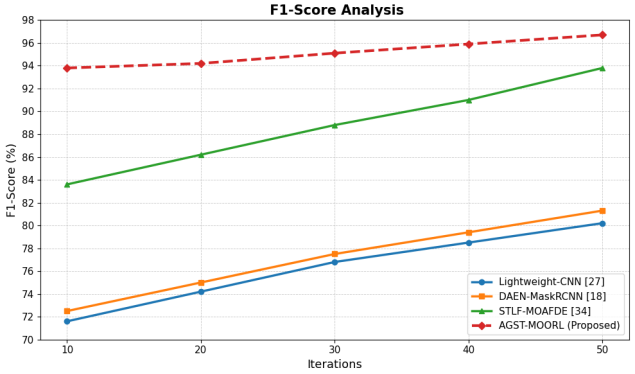


Figure 13: F1 Score Comparative Analysis

rejection of unsuitable fertilizer choices, enhancing decision reliability and supporting sustainable agricultural practices in real-time environments.

F1-Score

The F1-score results demonstrate the balanced performance of the AGST-MOORL model in handling both precision and recall effectively. At the 50th iteration, the proposed model achieves an F1-score of 96.7%, significantly higher than Lightweight-CNN (80.2%), DAEN-MaskRCNN (81.3%), and STLF-MOAFDE (93.8%) in clearly shown in Table 7 and Figure 13. This indicates that the model maintains low false positives and false negatives simultaneously. The steady improvement across iterations reflects stable convergence and consistent learning behavior. The integration of graph-based feature learning captures complex relationships, while reinforcement optimization continuously refines prediction decisions. In contrast, existing models struggle to balance precision and recall due to static learning mechanisms. Hence, AGST-MOORL ensures highly reliable and accurate classification performance.

Table 7: F1-Score Analysis

Iterations / Models [F1-Score]	*Lightweight-CNN*	*DAEN-MaskRCNN*	*STLF-MOAFDE*	*AGST-MOORL (Proposed)*
10th - Iteration	71.6	72.5	83.6	93.8
20th - Iteration	74.2	75	86.2	94.2
30th - Iteration	76.8	77.5	88.8	95.1
40th - Iteration	78.5	79.4	91	95.9
50th - Iteration	80.2	81.3	93.8	96.7

Table 8: Precision Analysis

Iterations / Models [Precision]	*Lightweight-CNN*	*DAEN-MaskRCNN*	*STLF-MOAFDE*	*AGST-MOORL (Proposed)*
10th - Iteration	72.5	73.3	84.5	93.4
20th - Iteration	75	75.6	87	94.1
30th - Iteration	77.5	77.9	89.5	94.9
40th - Iteration	79.5	80	91.5	95.8
50th - Iteration	81.5	82.1	93.4	96.5

Table 9: AUC-ROC Curve Analysis

Iterations / Models [AUC-ROC]	*Lightweight-CNN*	*DAEN-MaskRCNN*	*STLF-MOAFDE*	*AGST-MOORL (Proposed)*
10th - Iteration	0.39	0.42	0.55	0.67
20th - Iteration	0.43	0.44	0.59	0.69
30th - Iteration	0.47	0.48	0.63	0.70
40th - Iteration	0.51	0.52	0.65	0.74
50th - Iteration	0.56	0.55	0.67	0.78

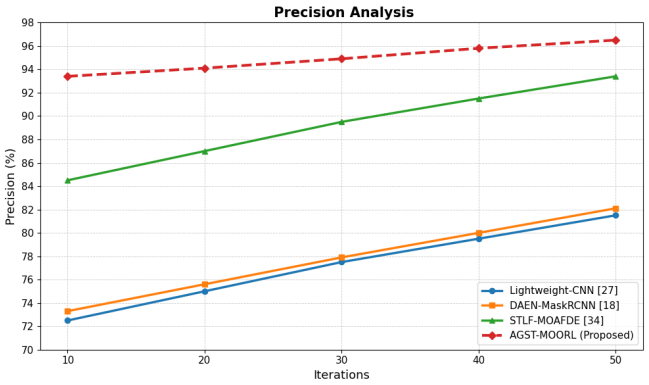


Figure 14: Precision Comparative Analysis

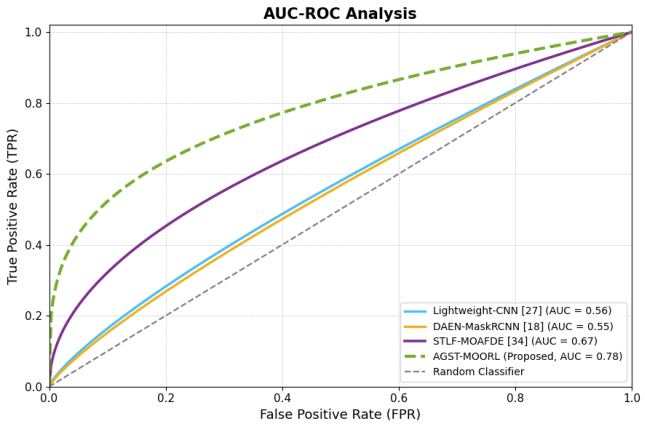


Figure 15: AUC-ROC Comparative Analysis

Precision

Precision evaluates how reliably the model's positive predictions correspond to truly optimal fertilizer recommendations. At the 50th iteration, AGST-MOORL achieves 96.5% precision, clearly exceeding Lightweight-CNN (81.5%), DAEN-MaskRCNN (82.1%), and STLF-MOAFDE (93.4%) is illustrated in Table 8 and Figure 14. This indicates that when the proposed model suggests a fertilizer strategy, it is highly likely to be correct. The improvement is not abrupt; precision steadily increases across iterations as the model refines its decision boundaries. The graph-based learning component groups similar agricultural conditions, reducing ambiguity in classification, while the reinforcement learning mechanism penalizes incorrect positive predictions through its reward structure. In contrast, baseline models tend to misclassify borderline cases due to limited adaptability. As a result, AGST-MOORL delivers more trustworthy recommendations, which is critical for minimizing unnecessary fertilizer usage and associated costs.

AUC-ROC

The AUC-ROC analysis evaluates the model's ability to distinguish between optimal and non-optimal fertilizer decisions across varying thresholds. At the 50th iteration, AGST-MOORL achieves an AUC of 0.78, outperforming Lightweight-CNN (0.56), DAEN-MaskRCNN (0.55), and STLF-MOAFDE (0.67) is portrayed in Table 9 and Figure 15. This indicates a stronger separation capability between classes and a lower probability of misclassification. The ROC curve for AGST-MOORL consistently lies above the baseline models, reflecting improved true positive rates with controlled false positives. The gradual increase in AUC across iterations highlights stable learning and enhanced decision boundary formation. The integration of graph-based representation enables better feature discrimination, while reinforcement optimization adjusts decision thresholds dynamically. In contrast, existing models show weaker separability due to static learning approaches, making AGST-MOORL more robust and reliable for real-time agricultural recommendations.

Ablation Study

The ablation study evaluates the contribution of each component in AGST-MOORL by systematically removing modules. When the graph-based learning (AGST) is excluded, accuracy drops by approximately 4–5%, indicating the importance of capturing inter-sample relationships. Removing the MOORL optimization further reduces performance by nearly 3%, highlighting its role in refining decision policies. A baseline model without both components shows the lowest performance, confirming the effectiveness of the integrated framework.

The impact analysis demonstrates that graph construction significantly improves feature representation by linking similar agricultural conditions, while temporal learning enhances adaptability to seasonal variations. The reinforcement module ensures balanced optimization

across yield, cost, and environmental factors. Together, these components lead to improved accuracy, recall, and stability across iterations. In terms of complexity, the AGST module operates with time complexity $O(N^2)$ for graph construction and $O(|E|)$ for graph convolution, where N is the number of samples and E represents edges. The MOORL component introduces iterative optimization with complexity $O(T \cdot A)$, where T is the number of episodes and A is the action space. Despite this, efficient batching and sparse graph representation ensure practical scalability for real-time deployment.

Conclusion

This research presents AGST-MOORL, a unified framework that combines adaptive graph-based spatio-temporal learning with multi-objective reinforcement optimization for intelligent fertilizer recommendation. The model integrates heterogeneous agricultural data, constructs a similarity graph to capture inter-field relationships, and learns temporal patterns to reflect evolving environmental conditions. The MOORL module further refines decisions by jointly optimizing crop yield, fertilizer cost, and environmental impact. Experimental results on 4700 integrated samples demonstrate consistent gains across all metrics, achieving 97.2% accuracy, 96.5% precision, 97.0% recall, 96.1% specificity, 96.7% F1-score, and an AUC-ROC of 0.78. Compared with Lightweight-CNN, DAEN-MaskRCNN, and STLF-MOAFDE, the proposed model shows faster convergence, lower misclassification, and stronger generalization. The confusion matrix confirms balanced performance across optimal and non-optimal classes. The key contribution lies in coupling relational learning with reinforcement-driven decision-making, enabling context-aware and adaptive recommendations. The framework supports real-time deployment with stable inference and scalable performance. Overall, AGST-MOORL advances precision agriculture by delivering accurate, reliable, and sustainable fertilizer strategies, thereby improving productivity while minimizing cost and environmental risk.

Limitations & Future Work

Current limitations include reliance on structured tabular data and a static similarity threshold during graph construction. The model does not explicitly incorporate long-range temporal sequences or spatial coordinates. Future work will explore dynamic graph learning, geo-spatial embeddings, and sequence models, along with field trials and edge deployment for low-latency, farm-scale real-time recommendations.

Acknowledgement

I would like to express my sincere gratitude to my respected guide, Dr. Priya R, Professor and Head, Department of Computer Science, Sree Narayana Guru College, Coimbatore, for her continuous guidance, valuable suggestions, and constant encouragement throughout this research work. Her insights and support have played a significant role in shaping this study. I extend my heartfelt thanks to the management and faculty members of the Department of Computer Science, Sree Narayana Guru College, K.G Chavadi, Coimbatore, Tamil Nadu, for providing the necessary academic environment and resources to carry out this research successfully. I also acknowledge the support received from my colleagues and well-wishers who contributed directly and indirectly to the completion of this work. Their encouragement and cooperation have been invaluable in achieving this research outcome. Finally, I express my deep gratitude to everyone who supported me during this research journey.

Author Credits

Basheer P, conceptualized the research problem, designed the AGST-MOORL framework, and carried out data acquisition, preprocessing, and model development. Implemented the graph-based learning and reinforcement optimization modules, conducted experiments, analyzed results, and prepared the manuscript draft, including figures, tables, and performance evaluation.

Dr. Priya R, provided overall supervision, research direction, and critical insights throughout the study. Contributed to methodological refinement, validation strategy, and interpretation of results. Reviewed and edited the manuscript, ensuring technical accuracy, clarity, and alignment with academic standards.

Declaration

During this research implementation, various tools are utilized to support development and presentation. Grammarly was used for language refinement, Mermaid Live Editor for diagram generation, and OpenAI tools for deriving selected equations. Python and Google Colab were employed for coding, model implementation, and experimentation. All outputs were carefully verified, and the intellectual contributions and interpretations remain entirely the authors' own.

Data Availability

The datasets and pseudocode used in this study are available from the corresponding author and will be provided upon reasonable request.

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