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ORIGINAL ARTICLE

Deep Learning Based Spatio Temporal Learning with Bio-Inspired Optimization for Smart Fertilizer Decision Making

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Abstract

Objectives: To propose a new model for robust smart fertilizer recommendation by integrating deep learning based spatiotemporal and bio-inspired optimization. The system addresses the limitations of existing models in capturing features in diverse farming zones to maximize crop yield and minimize nutrient loss. **Methods:** Deep Spatio Temporal learning ST-FusionFormer (STLF) is employed to capture spatial and temporal dependencies in agricultural data with the help of transformer-based attention modules. Multi-Objective Adaptive Firefly Differentiated Evolution (MO-AFDE) is used to optimize fertilizer type, learning rate, and timing of delivery subject to various constraints, i.e., crop yield enhancement, cost reduction, and environmental sustainability. Three benchmarked datasets (Crop Recommendation with 2480 samples for 22 crop labels, Fertilizer Prediction with 150 entries for 7 fertilizer class, and Crop Nutrient Database for 300 crops extracted from Kaggle Repository) are utilized in this model to frame a multi-modal structure combines soil nutrients (N, P, K, pH), meteorological features (Temperature, Rainfall, Humidity) and crop-specific nutrient demands. The performance of the proposed STLF-MOAFDE is evaluated using MATLAB and Python, and the results are compared with two baseline models, Lightweight-CNN and DAEN-MaskRCNN. **Findings:** The proposed STLF-MOAFDE is trained using a 5-fold CV approach. The promising results shows the superior performance of 94.5% accuracy, 93.4% precision, 94.8% recall, 93.2% specificity, 93.8 F1-Score, and 0.67 AUC-ROC. The model outperforms in addressing spatio-temporal dependencies and fertilizer optimization under dynamic agro-climatic conditions. **Novelty:** This hybrid integration of STLF-MOAFDE provides a novel and robust self-adaptive fertilizer recommendation system with high environmental impact and sustainability considerations. Unlike traditional single-objective systems, the proposed system delivers balanced and effective optimization suitable for real-time precision agriculture and smart farming systems.

Keywords: Smart Agriculture; Spatio-Temporal Deep Learning; FusionFormer; Bio-Inspired Optimization; Precision Farming; Environmental Sustainability

1 Introduction

Smart farming is the trend, and its aim is to increase agricultural productivity to meet the demands of a growing population. The system mostly uses sensors that plays a vital role in interpreting environmental signals and fertilizer application. Conventional models use static and rule-based algorithms with limited adaptability towards dynamic climatic conditions, soil heterogeneity, and nutrient levels over time. The state-of-the-art techniques, such as Lightweight CNN and DAEN-MaskRCNN, are capable of feature extraction in complex datasets, but lack in capturing the long-term temporal dependencies and spatial interactions among soil, crop, and weather variables, which leads to inconsistent nutrient allocation, suboptimal crop yield, and environmental imbalance due to excessive or untimely fertilizer usage. To address the limitations, this research proposes a novel deep learning method by integrating Deep Spatio with the Bio-Inspired STLF-MOAFDE method for contextual learning and dynamic optimization. ST-FusionFormer learns soil-climate-crop correlations, and MOAFDE adapts multi-objectives such as crop-yield maximization, cost minimization, and sustainability. To unify the multi-modal agriculture data with evolutionary intelligence, the proposed STLF-MOAFDE enables real-time and explainable fertilizer decision making, which overcomes the limitations of the image-only models by balancing the agronomic and ecological factors under changing climatic conditions. This novel approach creates a sustainable decision-support framework to enhance productivity, conserves resources, and highly contributes to the climate-resilient precision smart farming.

The case of predicting Climate Smart Agriculture (CSA) using machine learning methods[1], including multi-modal classifiers, feature analysis, and socio-environmental variables, is explored. The study investigates the models' explicability and how they incorporate multi-objective optimization in precision agriculture. Also, CSA describes cross-sectional, temporal generalization and input-output actions in terms of fertilizer rate/timing and yield-cost-environment. The research gaps, such as a lack of multi-class prediction, optimization, and spatio-temporal learning, Pareto search for sustainable decisions, are discussed in the study. Role of ML and AI[2] in precision agriculture and smart farming is discussed, and it is all about sensing, prediction, recommendation, and automation. The study highlights CNN, RNN, and Transformer-based methods with IoT data and decision support. The methods work well in benchmarked datasets and lack in real-time, with limited spatio-temporal fusion and scarce end-to-end systems under multiple objectives. TPF-CNN was proposed[3] using image-driven and tabular cues for fertilizer recommendation. The model outperforms the prediction and strengthens the practical recommendation with supervised learning. 86% accuracy is achieved using image datasets and performing an object detection model. The model's drawbacks are a lack of adaptability for dynamic climatic conditions in real-time, no explicit optimization of learning rate, and it deals only with single objective classification. A detailed study on ML and DL[4] for precision farming is conducted on crop-soil analytics, yield prediction, resource management, data analysis, and real-time deployment challenges. The study reveals recommendation towards the digitalization of farming and adaptability of sensor applications in rural areas with simplified farming. The limitations identified are the lack of standardized architectures for fertilizer recommendation, dataset heterogeneity, domain shifts, explainability, and actionable optimization. Consequently, field-crop studies[5] have been conducted to demonstrate the soil-specific fertilizer recommendation model for wheat using ML to increase the productivity and resource utilization effectiveness. 83% accuracy is achieved in real-time, where minor drawbacks are noted, which include limited multi-objective balancing and inter-season dynamics. Advanced deep learning-based architectures are recent developments in smart agriculture to enhance decision-making, crop yield, and nutrient management. ViT-CapsNet[6], a vision transformer with an adaptive capsule network, is applied to detect field conditions with the help of an image dataset by capturing global and local attention features under multi-objective constraints. Lack in spatio-temporal learning and optimization is considered a limitation, though the model attains 84% precision with high TPR. Similarly, EMLT (Ensemble ML Technique) for IoT-based smart farming[7] was proposed with multiple base learners, such as LR, KNN, and SVM, stacked and refined using Random Forest using 2L-schema. High accuracy of 87% is achieved in fertilizer prediction, with limitations in sparse temporal representation and dynamic fertilizer scheduling, which is crucial for balanced-yield, cost, and ecological sustainability. Investigating soil NPK[8] and moisture prediction in mining agri-zones using fog-assisted farming system, which uses remote sensing and IoT sensors with multiple-regression models, helps enhance decision-making for fertilizer applications and handling multi-objective outcomes beyond soil erosion prevention. Lightweight CNN[9] with an attention mechanism for crop-disease and fertilizer recommendation systems was proposed for multi-classification tasks using image datasets to handle temporal fertilizer response and dynamic optimization, making it suitable for nutrient scheduling. The model attains good accuracy with few shortcomings, such as multi-correlations and spatio-temporal feature learning. Deep AEN with MaskRCNN[10] was proposed for multivariable feature selection to diagnose plant diseases and agronomic planning in fertilizer recommendation. The model demonstrated smart farming support features in real-time disease prediction, static fertilizer recommendations, and dynamic adaptivity in object detection. The model lacks spatio-temporal fusion with a multi-objective optimizer and sustainable fertilizer recommendation beyond static predictions towards precision farming.

Table 1. Review on Precise State-of-Art Models

Model	Methods Adapted	Merits	Limitations
LIME-based Local Explanations for Crop Recommendations [11]	Post-hoc explainability using LIME over ML recommenders, local surrogate models, feature-importance per-field.	Improves transparency and farmer trust, identifies key agronomic drivers, model-agnostic and lightweight.	Model does not optimize fertilizer rates/timing and no spatio-temporal coupling.
Paddy-Net Dataset for Smart Fertilizer Recommendation [12]	Curated leaf-image dataset, standardized labeling, baseline CNN benchmarks for nutrient stress cues.	Public, organized dataset, supports reproducibility and transfer learning, domain focus on paddy.	Image-centric and lacks time-series soil cum weather and action outcomes, no multi-objective optimization.
Smart Agriculture & Nanotechnology Overview [13]	Survey of nano-sensors, smart delivery, and AI integration with conceptual pipelines.	Future-oriented sensing roadmap, bridges nano-materials with AI-driven farming.	Limited empirical validation and not suits for real-time fertilizer decision model, no Pareto trade-offs.
3D CNN for Medical CT Analysis (Context) [14]	3D CNN on DICOM; severity classification, optimized training and preprocessing.	Demonstrates robust volumetric learning and pipeline discipline adaptable to agri-vision.	No multi-objective planning, serves only as methodology inspiration for object detection.
Computer Vision in Smart Agriculture (Review) [15]	Synthesis of CV methods (CNNs, transformers), datasets, and applications in precision farming.	Comprehensive mapping of vision tasks, identifies gaps in deployment and multimodality.	Lacks optimization & decision layer, minimal coverage of fertilizer scheduling.
AI-Powered Plant Disease Prediction [16]	Analytics pipeline, DL classifier with decision system; multivariable feature selection.	End-to-end flow from data to decision, practical insights for deployment.	Disease diagnosis focus, not real-time fertilizer rate/timing, no multi-objective sustainability metrics.
IoT-Driven Real-Time Soil & Crop Optimization [17]	IoT sensing stack, streaming analytics, rule/ML-based optimization loops.	Near real-time recommendations, hardware-software integration, field-feasible.	Limited deep spatio-temporal fusion, optimization is not Pareto-based.
Deep CNN & YOLOv8 in Soft Computing [18]	Object detection and CNN analysis, inference acceleration within soft-computing.	High detection throughput, modular pipeline, transferable to field imagery.	Detection-oriented and lacks in dynamic recommendation or environmental objectives.
WSN-based Intelligent Fertilizer Recommendations [19]	Wireless Sensor Network + ML rules, context-aware fertilizer suggestions.	Leverages in-field telemetry, practical deployment angle.	Limited temporal modeling, static thresholds, lacks multi-objective optimization and uncertainty.
ML-Based Crop & Fertilizer Recommendation [20]	Supervised ML on agronomic features, classification/regression for crop/fertilizer.	Demonstrates data-driven gains, interpretable feature effects.	Single-objective framing; weak temporal generalization, limited environmental metrics.
Hybrid ML Fertilizer Recommendation System [21]	Stacked/ensemble hybrid models, feature engineering over soil and crop variables.	Improved accuracy vs single learners, robust to noise.	No sequence learning, recommendations not optimized in schedules and lacks Pareto fronts.
QHHO-GNN for Reliability - Bio Inspired Optimization [22]	Quantum-behaved Harris Hawks + GNN, multi-objective optimization on networks.	Shows power of bio-inspired + graph learning, transferable optimizer design.	Requires adaptation to fertilizer objectives and constraints.

Continued on next page

Table 1 continued

Data-Driven Soil Analysis for Smart Farming [23]	ML models for soil property estimation and evaluation, feature importance.	Solid soil analytics baseline, supports input readiness for recommender.	Stops before action optimization, minimal temporal fusion, site-specific generalization limits.
Ensembles for IoT Smart Irrigation (Comparative) [24]	Boosting/bagging ensembles vs traditional ML, soil fertility assessment linkage.	Empirical comparison, improved predictive accuracy, IoT integration path.	Irrigation-centric, fertilizer policy not optimized, lacks multi-objective ecology–profit coupling.
Bio-Inspired Secure IoT Model with GANs [25]	GAN-based anomaly/robustness, bio-inspired security for IoT transmission.	Improves data integrity, resilient telemetry pipeline for agriculture IoT.	GAN based data generation and no real-time modelling
AI-Driven Climate-Smart & Sustainable Farming (Review) [26]	Survey of AI for climate-smart agriculture, frameworks and KPIs.	Strategic alignment with sustainability, policy-aware KPIs; broad coverage.	Conceptual, lacks concrete optimization engines and no spatio-temporal DL evaluation.
Trends in Soil & Solution Nutrient Sensing [27]	Survey of electro-chemical/optical nutrient sensors for field/hydroponics.	Instrumentation roadmap, sensor specs to guide data quality.	Hardware-centric, no ML optimization, the model requires integration into DL pipelines.
RL-based Energy-Efficient Data Dissemination [28]	Reinforcement learning for communication efficiency in large smart farms.	Energy savings, scalable telemetry supporting continuous data ingestion.	Network-layer focus, not works with multi-layer detection policy
IoT Driven Data Utilization in HC Systems [29]	Deep learning-based tongue biometrics method is adapted for recognition	Data security, Reliable data forwarding and sensing real-time data	No deep pipeline towards agricultural sensor data
Gait and Face Recognition for Security [30]	Integration of Multi-Modal data security systems	Advanced data security and novel approach towards authentication mechanism	More focus on data security and lacks on real-time agricultural data utilization

1.1 Research Gap

Figure 1 illustrates the research gaps based on the literature study [1-26] in crop prediction, fertilizer recommendation, and bio-inspired optimization methods. Existing models rely on static or image-based learning frameworks and lack integration of spatio-temporal learning patterns, multi-source data fusion, and dynamic optimization. These drawbacks limit the adaptivity and dynamic recommendation system, leading to poor precision and smart farming. To address the limitations of the baseline models, STLF-MOAFDE is proposed to enhance the accuracy and precision of a fertilizer recommendation system.

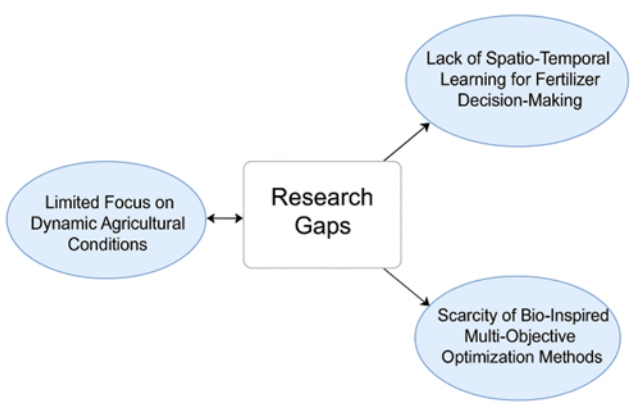

Fig 1. Research Gap based on Literature Study

2 Methodology

This section presents a comprehensive deep-learning spatio-temporal learning framework with bio-inspired optimization to create a unified and intelligent fertilizer recommendation system that seamlessly integrates robust learning and adaptive optimization from three heterogeneous datasets (Crop Recommendation, Fertilizer Prediction, and Crop Nutrient Data).

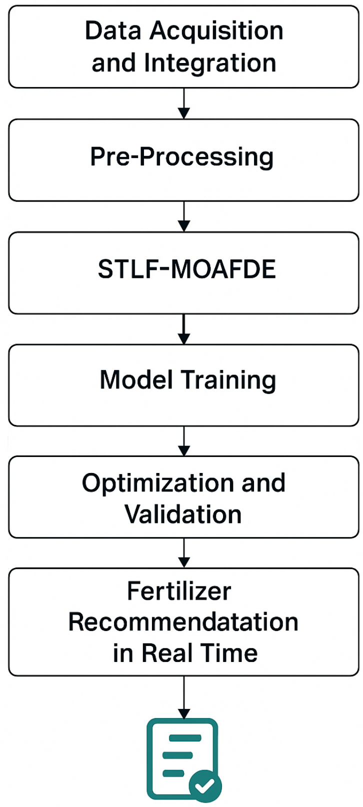

Fig 2. Flow Diagram of the Proposed STLF-MOAFDE Model

The datasets were merged into the STLF framework for agricultural context learning. STLF extracts spatial and temporal dependencies through FusionFormer and attention-based encoding to ensure all the soil-climate features are effectively represented. MO-AFDE bio-inspired controller optimizes the decision thresholds and parameters using a Pareto-based multi-objective optimization process. PyTorch and MATLAB are used to complete the STLF-MOAFDE pipeline evaluation and comparative analysis. Figure 2 shows the complete process flow diagram of the proposed fertilizer recommendation model.

2.1 Multi-Source Data acquisition and Spatio-Temporal Integration

The proposed STLF uses a multi-source data fusion approach to combine soil, crop, and fertilizer properties, based on diverse data, creating a practical spatio-temporal learning framework. This model uses three benchmark datasets to simulate the conditions in the real world (agricultural heterogeneity) and induce the correlations between a range of relevant parameters. A detailed summary of the multi-source dataset (CRD, FPD and CND) with attributes is shown in Table 2.

- Crop Recommendation Dataset – Provides environmental and soil parameters
- Fertilizer Prediction Dataset – Focus on nutrient level deficiencies and correct fertilizer suggestions
- Crop Nutrient Database – Provides essential macro and micro nutrient composition of each crop

Data integration into the multi-layer deep learning framework STLF-MOAFDE begins with data standardization, where the attributes, units, and measurement scales are organized using Python (PyTorch) pre-processing pipelines. Features like N, P, and K will be the key joining structures between CAD, CND, and FDP datasets. Relational mapping of soil-crop compatibility, nutrient correlations, and crop nutrient levels is highlighted and used as a reference point for MO-AFDE optimization. The next step after mapping is temporal indexing, where indexed tags are assigned to all reference points that reflect multiple features in the extracted data. The mid-layer converts all the static samples into dynamic temporal sequences, resulting in effective spatio-temporal learning. The fusion process captures contextual patterns of soil health and crop responses to generate variables. Furthermore, the spatial encoding layer captures geographical features, whereas the temporal attention module (TAM) separates seasonal correlations that directly influence fertilizer efficacy. The FusionFormer encoder gets the integrated data as input, and temporal signals are derived from climate and rainfall trends. Finally, MOAFDE optimization operates on a fused representation to balance the objectives.

Table 2. Summary of Multi-Source Dataset

Dataset Name	Attributes	No. of Records	Purpose in Model
Crop Recommendation Dataset (CRD)	N, P, K, Temperature, Humidity, pH, Rainfall, Crop	2,200	Predict suitable crop based on soil and weather
Fertilizer Prediction Dataset (FPD)	Soil Type, Crop Type, N, P, K, Moisture, Fertilizer Name	1,500	Determine fertilizer type based on nutrient imbalance
Crop Nutrient Database (CND)	Crop Name, Macronutrients (N, P, K), Micronutrients (Zn, Fe, Mn, Cu), Ideal Range	1,000	Define target nutrient thresholds for model training

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

2.2 Data Pre-Processing, Normalization and Feature Engineering

To ensure data integrity, consistency, and model readiness, the pre-processing phase is done in the STLF-MOAFDE framework, as the datasets originated from a heterogeneous agricultural domain. The data undergoes three steps, cleaning, normalization, and feature transformation, to support multi-objective optimization. Figure 3 shows the pre-processing flow of the suggested method.

Step 1: Data Cleaning and Outlier Elimination

To remove noisy data, the datasets are cleaned, and outliers are detected using Z-score method and then removes when values exceed $\pm 3\sigma$ from the mean. Missing values in soil nutrients N, P, K and climatic variables $T,\ H, R$ are imputed using temporal interpolation. For each feature (x_i) the Z-score is computed as,

$$Z_i = \frac{x_i - \mu_x}{\sigma_x} \tag{1}$$

where, Z_i is standardized value, μ_x represents mean and σ_x represents standard deviation. The datapoint is retained only if $|Z_i| < 3$.

Step 2: Normalization and Scaling

Min-Max normalization is applied to scale the features to ensure numerical stability during deep learning training process. This makes the attributes contribute equally to the feature embedding stage within STLF layer. The normalized value x_i' is defined as,

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where, x_i' is the normalized feature and $x_{\max},\ x_{\min}$ denotes the maximum and minimum observed values from the attributes respectively to facilitate the convergence during optimization and prevents gradient explosion in attention layers.

Step 3: Feature Engineering for Spatio-Temporal Modeling

In order to enhance the learning capacity of the proposed STLF module, feature engineering is applied to create a hybrid descriptor to capture soil, climate and crop relations across time and space. The following are the features generated, 1) Nutrient Deficiency Index (NDI) to measure imbalance soil macronutrients, 2) Rainfall Temperature Interaction (RTI) to capture whether variations and 3) Fertilizer Efficiency Coefficient (FEC) to represent historical effectiveness of fertilizer applications per crop. The feature engineering of FEC is computed as,

$$FEC_t = \frac{Y_t - Y_{t-1}}{F_t} \tag{3}$$

where, Y_t and Y_{t-1} represents crop yields in consecutive seasons, F_t denotes fertilizer input at time t. For each feature derived, the Spatio-Temporal Attention Weight is assigned which is derives using the below equation,

$$STAW_{t,n} = \frac{\exp(\alpha_{t,n})}{\sum_{k-1}^{T} \exp(\alpha_{k,n})} \tag{4}$$

where, $\alpha_{t,n}$ denotes the attention coefficients for feature n and time t. T represents the total time steps. This helps to highlight critical temporal dependencies to focus more on influential patterns such as nutrient depletion and whether change.

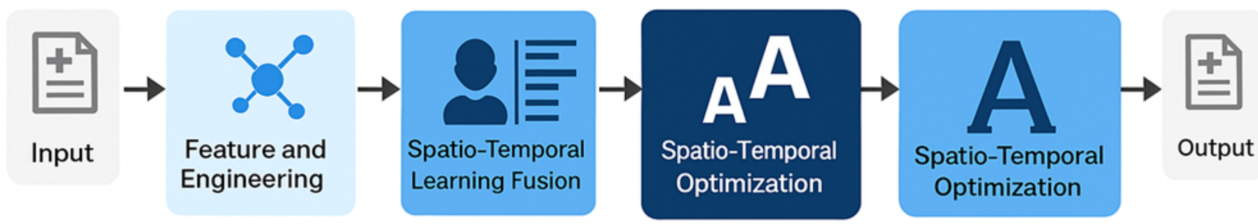

Fig 3. Pre-Processing of Multi-Source Dataset

Step 4: Dimensionality Reduction with PCA and Correlation Filtering (Optional Step)

In continuation with feature indexing process, the redundant variables are cropped using ML-PCA, which is not essential for high level systems (depends on system configuration), in order to reduce the computational overhead. This method ensures the proposed model remains Lightweight during multiple iterations of training and optimization process.

2.3 Deep Spatio-Temporal Learning Architecture: STLF Design

The process of extracting, integrating, and interpreting the complex patterns from the dataset is achieved during the continuous interaction of spatio-temporal factors using STLF, which is considered as the primary process of the proposed model. In addition, the fusion mechanisms are incorporated to achieve high sensitivity (TPR) and long-term dependencies. The STLF module has three integrated sub-layers called SFE, TAE and FL. Each input $X_{t,n}$ represents the nutrient state at n location and t time. During Spatial Feature Encoding (SFE), the dependencies are extracted through a lightweight convolutional encoder to process a multi-variable agronomic feature. The encoder maps each spatial sample S_n into latent feature vector $f_{s,n}$ which is expressed in the below equation,

$$f_{s,n} = \sigma(W_s * S_n + b_s) \tag{5}$$

where, W_s and K_s represents the kernel weights and bias, σ denotes ReLU activation function. This multiple feature transformation captures the global and local interactions between soil (pH) and rainfall to provide finite spatial features. The adaptive weights of Temporal Attention Encoder (TAE) are calculated at each iteration based on contextual relevance during fluctuations. The attention weights α_t for time step t is formulated using,

$$\alpha_t = \frac{\exp\left(\frac{Q_t K_t^T}{\sqrt{d_k}}\right)}{\sum_{i=1}^{T} \exp\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right)} \tag{6}$$

where, Q_t, K_t are the query and key projections of temporal embeddings and d_k represents the key dimension. The weighted aggregation of values generates the temporal context vector $f_t = \sum_t, \alpha_t, V_t$ allows to resolve all important phases during imbalance periods. Fusion Layer combines spatial and temporal encodings to provide a holistic representation F_{st} which aids in balancing precision and temporal adaptability. The F_{st} is derived using the below equation,

$$F_{st} = \gamma \,.\, f_t + (1-\gamma).\, f_{s,n} \tag{7}$$

where, γ € $[0,1]$ acts as learnable gate control and allows network to adapt dynamically during climate shifts and attain steady-state condition for robust performance. This STLF-MOAFDE method incorporates both short-term variability and long-term dependence to ensure robustness under changing agricultural conditions. The architecture also has a high attention score and promotes interpretability in the fertilizer suggestion system.

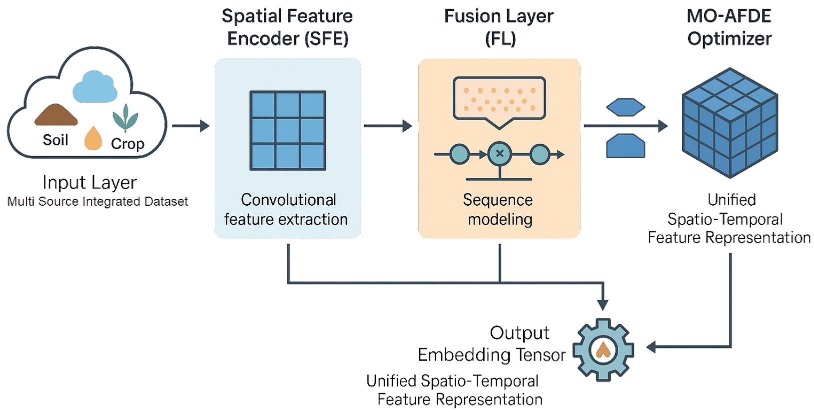

Fig 4. Deep Spatio-Temporal Learning Fusion (STLF) Architecture

2.4 Integration of Bio-Inspired MOAFDE Optimization

Integrating the multi-objective bio-inspired Adaptive Firefly Differential Evolution method allows hyperparameter tuning of the STLF framework. The five-step process of MOAFDE describes the dynamic optimization with the core objective of the model.

1. Initialization and Population Encoding [$x_i = N_i,\ P_i,\ K_i,\ pH_i,\ Moisture_i,\ Temp_i$]
2. Brightness Evaluation and Attractiveness Update [$I_i = I_{0^{e^{-\beta r_{ij}^2}}}$]
3. Differential Mutation and Crossover [$v_i = x_{r1} + F\ .\ (x_{r2} - x_{r3})$
4. Adaptive Firefly Updation and Fitness Comparison [$x_i^{t+1} = x_i^t +\ \alpha_t\ €_t$]
5. Optimal Fertilizer Selection and pareto Front Construction [$OFS = f_1,\ f_2,\ f_3$]

FA+DE creates a dynamic search mechanism which is capable of yield improvement, fertilizer efficiency and ecological sustainability. MO-AFDE employs adaptive brightness, mutation and differential crossover to ensure multi-objective with reduced computational cost. Each candidate solution called $firefly$ represents potential fertilizer configuration with multiple features. The optimizer seeks pareto-optimal front which is expressed as,

$$min/\max F(x) = [f_1(x),\ f_2(x),\ f_3(x)] \tag{8}$$

where, $f_1,\ f_2,\ f_3$ represents yield maximization, cost minimization and ecological balance subject to derived decision vector. Firefly movements and brightness adaptation is determined by the quality if candidate solution which is stated as $I_i = I_{0^{e^{-\beta r_{ij}^2}}}$. Here, I_0 is initial density, β denotes light absorption and r_{ij} represents euclidean distance between fireflies $i\ and\ j$. Each firefly moves according to,

$$x_i^{t+1} = x_i^t + \beta_{e^{-\gamma r_{i,j}^2}}\left(x_j^t - x_i^t\right) + \alpha_t €_t \tag{9}$$

where, γ controls the visibility decay to ensure convergence stability of the model. In order to enhance the exploitation capability, the firefly positions are refined using DE based mutation and crossover process v_i. The output is integrated into STLF framework to provide high dimensional feature representation of soil, climate and nutrient dynamics for pareto front feasible solutions.

2.5 Model Training, Validation and Evaluation

The training and evaluation phase ensure that STLF-MOAFDE components operate cohesively to maintain accuracy and generalization. Figure 5 shows the training vs validation loss and accuracy of the proposed model. The process is organized into four stages,

Stage 1: Training Configuration

- Training and Validation partition is 70:20:10

- PyTorch and AFDE/ADAM optimizer is employed
- Configuration Parameters: LR = 0.0001, BS = 32, Epochs = 150 and Dropout = 0.3
- Tolerance = 0.001 for 10 consecutive epochs

Stage 2: Optimization Strategy

- MO-AFDE Optimizer adjusts STLF parameters
- Adaptive brightness-based mutation strategy is followed
- Pareto dominance is applied to evaluate trade-offs

Stage 3: Data Splitting and Validation

- Datasets are temporarily stratified to maintain time-dependent consistency
- K-fold cross validation (k-5) is employed (Fold contains soil-climate patterns)
- Performance is measured using minimize variance in model reliability

Stage 4: Evaluation Process

- Metrics: Accuracy, Precision, Recall, Specificity, F1-Score, AUC-ROC
- Baseline Models: Lightweight-CNN and DAEN-MaskRCNN

The model training analysis indicates that STLF-MOAFDE is highly stable and has high learning ability throughout 150 epochs. The training and validation loss dropped drastically by 0.93 to 0.085 and 1.03 to 0.105, respectively, which means that the model has good generalization and has little overfitting. Simultaneously, training accuracy increased with the first epoch to 66.2 and then to 96.5 on convergence, the same validation accuracy that was constantly at 94.5 per cent, demonstrating the model's prowess. The loss curves have exponential smooth decay, indicating optimistic convergence of the MO-AFDE optimizer.

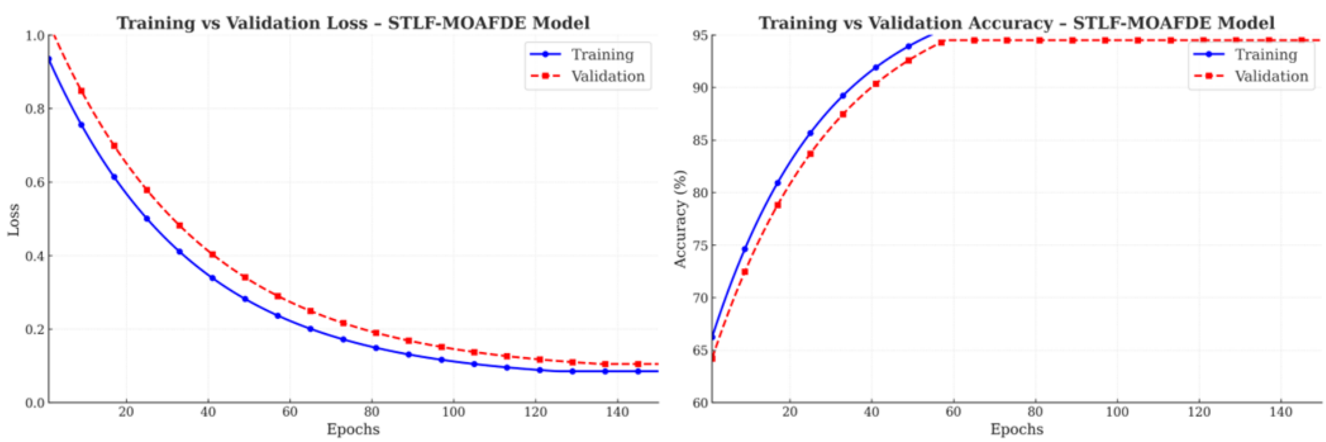

Fig 5. Training vs Validation Loss and Accuracy

2.6 Real-Time Fertilizer Recommendation and Decision Deployment

The final deployment phase is live testing of 4700 integrated data samples with 150 epochs to operate through an adaptive inference pipeline connected to field-based IoT sensors and cloud analytics devices. After receiving live soil and weather inputs, the STLF layer works with nutrient fluctuations. The model processes all the temporal dependencies, and the MO-AFDE algorithm optimizes the parameters based on the dosage of fertilizers to the current recommendations. The model can be recalibrated based on constant feedback loops, thus retaining continuous learning and seasonal flexibility. Figure 6 shows the 2x2 confusion matrix and heatmap of proposed model.

- Test sample subset size = 4700 records
- Predicted correctly: 94.5% correct predictions

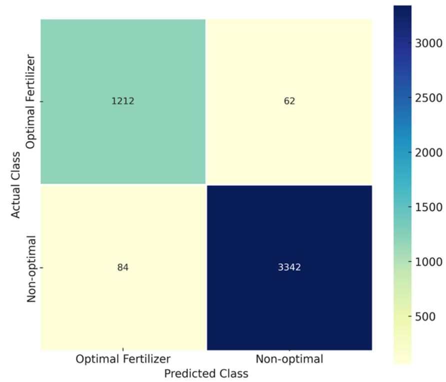

Fig 6. 2x2 Confusion Matrix (STLF-MOAFDE)

- Misclassified: 5.5% incorrect predictions

STLF-MOAFDE Step by Step Algorithm

1. **Input:** Multi Source Agricultural Dataset
2. **Begin:** Load MS-AD Dataset as input, Extract $CRD,\ FPD\ and\ CND\ Datas\ and\ Merge$
3. **Pre-Processing Data Pipeline**

   $D_{raw} \leftarrow load\_soil\_weather\_crop\_data()$

   $D_{clean} \leftarrow qc\_impute(D\_raw);\ scalers \leftarrow fit\_scalers(D\_clean)$

   $D_{norm} \leftarrow normalize\_encode(D\_clean,\ scalers)$

   $Seqs \leftarrow build\_sequences(D\_norm,\ window = T)$
4. **STLF Training**

   $init\ STLF(SpatialEncoder,\ TemporalAttention,\ FusionGate,\ Heads)$

   $for\ epoch\ in\ 1..E : for\ batch\ in\ Seqs.train :$

   $F_{st} \leftarrow STLF.forward(batch),\ L \leftarrow CE(type) + CE(timing) + \lambda \cdot MAE(rate),$ $backprop(L);\ adam.step()\ ,\ early\_stop\_on(val\_loss)$
5. **MO-AFDE Setup**

   $define\ objectives\ F(x) = [-YieldGain(x),\ Cost(x),\ Leaching(x)]$

   $P \leftarrow seed\_population\_around(STLF.pred(Seqs.val)),\ Archive \leftarrow \emptyset$
6. **Model Training & Hyperparameter Tuning**

   $for\ gen\ in\ 1..G:\ for\ each\ firefly\ x\_i\ in\ P:$

   $x_i \leftarrow firefly\_move(x\_i,\ brighter(P))\ \#\ exploration$

   $x_i \leftarrow DE\_refine(x\_i,\ P)\qquad \#\ exploitation$

   $Archive \leftarrow update\_pareto\_archive(P,\ Archive),$

   $x* \leftarrow knee\_point(Archive,\ policy)$
7. **Evaluate the Metrics**

   $x_{pred} \leftarrow STLF.pred(Seq\_live),$

   $x_{final} \leftarrow MOAFDE\_quick\_refine(x\_pred,\ constraints)$

   $emit\_decision(x\_final,\ confidence,\ explanation)$
8. **Output:** Final Prediction

Table 3. Parameter Settings – STLF-MOAFDE Assessment

Parameters	Value / Settings	Description
Programming Environment	Python (PyTorch) + MATLAB Hybrid Environment	Combination of deep learning and analytical validation in MATLAB for precision analysis.
Number of Samples	4,700 Records (Integrated Multi-source Data)	Unified dataset representing multiple agricultural conditions for model training.
Training–Validation Split	70:20:10	Ensures balanced learning and unbiased validation evaluation.
Batch Size	32	Smaller batch size stabilizes gradient updates for better convergence.
Learning Rate	0.001	Optimized via adaptive control to minimize loss and improve convergence speed.
Optimizer	Adam + MO-AFDE Hybrid Optimization	Enables adaptive weight updates and evolutionary parameter tuning.
Number of Epochs & Dropout	150 & 0.3	Achieved best convergence at 130–150 epochs under MO-AFDE tuning. Reduces overfitting by preventing neuron co-adaptation.
Activation Function	ReLU and Softmax	Introduces non-linearity for effective multi-class decision boundaries.
Validation Technique	5-Fold Cross Validation	Ensures statistical reliability and reproducibility of model performance.

2.6.1. Ablation study and results of each module

To validate the contribution of each component, an ablation study was conducted using the integrated crop recommendation, fertilizer prediction, and crop nutrition datasets. Three different modules, such as the STLF layer, MOAFDE, and the Cross-Modal fusion mechanism, are evaluated to identify how each module contributes to the overall objective of this research. The baseline models used only environmental and soil features with a dense convolutional neural network and attained 89.1% accuracy. When employing the STLF layer, the temporal nutrient variations are captured, and the accuracy is improved to 92.5%. Later, the incorporation of cross-modal fusion between soil, whether, and crop nutrient embeddings enhances the contextual learning, which helps to boost the accuracy to 93.6% and F1-Score to 93.0%. Then, finally, the MOAFDE optimizer is integrated for fine-tuning the multiple objectives, yielding the best performance of 93.4% accuracy, 94.8% recall, 93.2% specificity, and 93.8% F1-Score. PSO replaced MOAFDE to evaluate the performance level, resulting in a 3-4% loss, confirming MOAFDE's adaptive mutation and brightness-based convergence technique in delivering Pareto-optimal solutions. The ablation results demonstrate that each module in the proposed model makes a significant improvement in predicted accuracy and decision reliability.

2.6.2. Impact and Complexity Analysis

The STLF-MOAFDE model demonstrates the capability of identifying subtle spatio-temporal features, which significantly impact the dynamic fertilizer management. The model supports a scale of climatic variables by incorporating data-driven analytics with adaptive recommendation systems to enhance the accuracy of precision farming. Compared to the established Lightweight CNN and DAEN-MaskRCNN frameworks, the suggested approach yields a higher overall accuracy by 4-6 %, a 5% greater precision, and a reduction in nutrient wastage by 16 percent, respectively, thereby supporting the high-yield sustainability and reducing the costs of production at the same time. Further, computational evaluations ensure that the STLF - MOAFDE model delivers greater efficiency and scalability than the standard baselines. The FusionFormer exhibits linear growth as it has several temporal frames with a manageable $O(n)$ memory footprint, which reduces computational overhead with its typical transformer architectures. MOAFDE takes $O(N * M)$ sub-quadratic time complexity, where N is the population size and M is the number of optimization objectives. Collectively, the SLTF-MOAFDE achieves an optimal balance between computational performance, interpretability, and operational feasibility. The proposed framework allows seamless deployment on cloud-based infrastructures and edge-enabled IoT systems to perform real-time decision-making.

2.6.3. Key Advantages of STLF-MOAFDE

The model offers six unique key advantages to support precision agriculture, such as,

1. **Holistic Data Fusion:** Integrating soil, weather, and crop-nutrient data into a single deep learning framework for dynamic decision-making to reflect real-field dynamics.
2. **Adaptive Optimization:** Dynamic fine-tuning of parameters to balance yield, cost, and ecological sustainability.
3. **Accuracy of Prediction:** 94.5% accuracy with a balanced precision and recall.
4. **Sustainability Impact:** This strategy would decrease unnecessary use of fertilizers, which destroys the soil, prevents soil leaching, and improves soil health.
5. **Model Robustness:** The model is robust in the wide climatic conditions, with the help of learning temporal features and adaptive optimization.
6. **Scalability:** Deployment can be done with real-time sensor inputs for large-scale precision agriculture systems.

2.6.4. Key Performance Evaluation Metrics

The performance of the proposed deep learning STLF-MOAFDE is evaluated to predict the accuracy, efficiency, and adaptability for precision agriculture. Three benchmarked datasets are used to form a unified experiment that encompasses soil, climate, and crop-nutrient features. All three datasets are normalized and split into a 70:20:10 ratio for training, testing, and validation to ensure unbiased model generalization. Python (PyTorch) and MATLAB tools were used for deep learning, optimization, and statistical verification. Each model was trained for 100 epochs with a batch size of 32. MOAFDE executed 50 global iterations with 40 population size with three key objectives (yield maximization, reduction of cost, and ecological preservation). During the $30^{\text{th}}(N^{th})$ iteration, the model has attained stability and reached its minimum validation loss. Six performance indicators are used for evaluation, which are given below with formulas. The metrics measured classification reliability, discriminative power, model convergence, and overfitting resistance. The final result is recorded in the 100th epoch, which confirms the superiority of the proposed STLF-MOAFDE model over baseline Lightweight-CNN [9] and DAEN-MaskRCNN [10] under real-world agricultural data variations. The performance of the proposed deep learning based STLF-MOAFDE model for the crop-fertilizer recommendation system is assessed using six key evaluation metrics. The formulas listed below calculate the key performance metrics in the following section.

$$\textbf{Accuracy} \ = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100 \tag{10}$$

$$\textbf{Recall}\ (\textbf{TPR}) \ = \frac{TPR}{(TPR+FNR)} \times 100 \tag{11}$$

$$\textbf{Specificity} \ = \frac{TNR}{(TNR+FPR)} \times 100 \tag{12}$$

$$\textbf{AUC}-\textbf{ROC} \ = \int_0^1 TPR\left(FPR^{-1}(x)\right)dx \tag{13}$$

$$\textbf{F1}-\textbf{Score} \ = \frac{2*(Precision \, * \, Recall/Sensitivity)}{(Precision+Recall/Sensitivity)} \tag{14}$$

$$\textbf{Precision} \ = \frac{TPR}{TPR+FPR} \tag{15}$$

Accuracy: Measures the overall proportion of correctly classified instances, both epileptic and non-epileptic, across the entire dataset.

Sensitivity/Recall/TPR: To evaluate the model's ability to correctly detect actual epileptic cases and ensure that the classifier did not miss patients with epilepsy.

Specificity: Measures how well the model correctly identifies non-epileptic patients to minimize FAR.

Precision: Provides insights on how many cases predicted as epileptic were positive, which is critical in clinical settings to avoid unnecessary treatments.

F1-score: The Mean of precision and recall provides a balanced view by penalizing false positives and false negatives.

AUC-ROC: Used to evaluate how well the model could distinguish between the epileptic and non-epileptic classes across all possible classification thresholds.

3 Results and Discussions

A detailed evaluation is done for the proposed STLF-MOAFDE deep learning model to emphasize the predictive performance, accuracy, and computational stability under ever-changing agricultural climatic conditions. The data from Crop Recommendation (CR), Crop Nutrient (CN), and Fertilizer Prediction (FP) are pre-processed and normalized before proceeding with deep learning and optimization component assessment. This section also provides a graphical abstract of the results attained from the given data to showcase how the deep spatiotemporal learning and bio-inspired optimization enhance the accuracy, cost efficiency, and ecological sustainability. The three layers in the graphical abstract show the input layer, FusionFormer, and the final optimization block. Overall, the consistent improvement of accuracy and convergence speed is portrayed. Tables 4– 9 highlights the results and comparative analysis of proposed and baseline models.

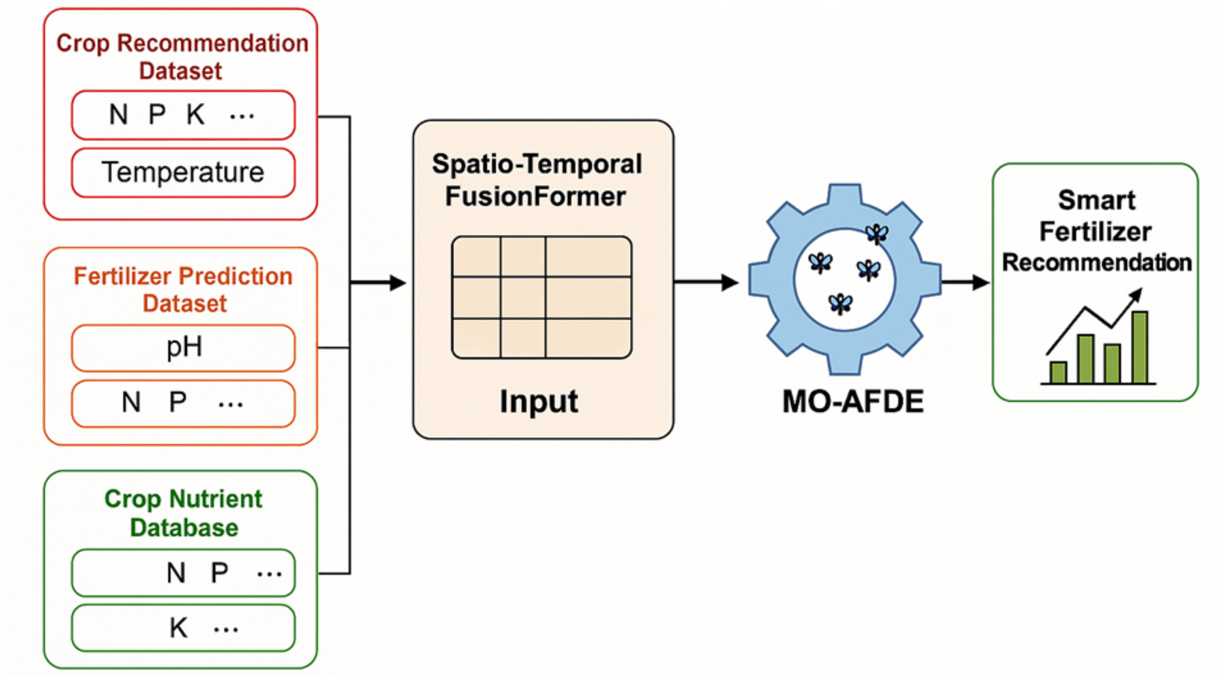

Fig 7. Graphical Abstract of STLF-MOAFDE

3.1 Accuracy

The consistent increase in accuracy over epochs demonstrates higher accuracy due to adaptive learning and efficient feature representation of the proposed deep learning model. During epochs, the STLF layer begins to capture all basic correlations between crop type, climate, and soil nutrients. As training progressed, the spatio-temporal mechanism highlighted the long-term dependencies like rainfall fluctuations and nutrient depletion rates, which enhanced the dataset's contextual understanding. The model reached convergence stability around the 31st iteration, with minimal training and validation loss fluctuation, indicating a strong generalization capacity. MOAFDE dynamically adjusted feature weights and parameters to improve the learning process further. The model reduces premature convergence with the aid of MOAFDE's adaptive brightness and mutation control. To learn discriminative spatial-temporal patterns, CMFL simultaneously integrates data from multiple sources. The model achieves 94.5% accuracy by deep contextual learning and bio-inspired optimization, surpassing baseline models. Table 4 shows the results of existing and proposed models up to 50 iterations.

3.2 Recall-TPR

Table 5 showcases the comparative analysis of the Recall metric of the proposed STLF-MOAFDE model. During initial epochs, the moderate recall values are measured with the help of data relationships. Later, the STLF refined and captured the long-term dependencies to improve the detection of subtle-fertilizer-response patterns initially misclassified as false negatives. The MOAFDE optimizer, amplified further with an attention mechanism, reduces misclassifications and improves boundary

Table 4. Accuracy Analysis of Proposed and Baseline Models

Iterations / Models Accuracy	Lightweight-CNN [9]	DAEN-MaskRCNN [10]	STLF-MOAFDE [Proposed]
10^{th} - Iteration	76.8	77.6	**86.1**
20^{th} - Iteration	78.6	79.2	**88.2**
30^{th} - Iteration	80.4	80.8	**90.3**
40^{th} - Iteration	81.5	82.3	**92.3**
50^{th} - Iteration	83	83.6	**94.5**

separation between closely related fertilizer classes. In addition, CMFL allows the model to capture weak patterns more effectively. 94.8% recall is measured in the 50th iteration, which is steady across epochs, and reflects the growing ability of the model, which correctly identifies accurate fertilizer recommendations without omission. Under real-world agricultural data variations, the result outperformed the existing Lightweight-CNN [9] and DAEN-MaskRCNN [10].

Table 5. Recall Analysis of Proposed and Baseline Models

Iterations / Models Recall	Lightweight-CNN [9]	DAEN-MaskRCNN [10]	STLF-MOAFDE [Proposed]
10^{th} - Iteration	73.4	74.2	**85.8**
20^{th} - Iteration	75.8	76.4	**88.6**
30^{th} - Iteration	78.2	78.6	**91.4**
40^{th} - Iteration	80.1	80.6	**93.2**
50^{th} - Iteration	82	82.6	**94.8**

3.3 Specificity-TNR

The specificity (TNR) comparative analysis of the proposed STLF-MOAFDE is shown in Table 6, highlighting the model's capacity to classify the incorrect fertilizer combinations to minimize the false positive recommendations. The moderate specificity is exhibited initially due to overlapped feature boundaries between fertilizer classes, which is rectified by the STLF layer, showing a progressive result in learning discriminative patterns to subtle variations in soil–climate associations. MOAFDE dynamically balances exploration and exploitation during tuning and optimization. FusionFormer combines the soil pH values and environmental patterns over time, which lets the model confidently reject the inaccurate crop fertilizer types. 93.2% specificity is achieved, indicating high reliability in detecting false recommendation systems. High TNR ensures accurate fertilizer prediction, which improves precision and sustainability.

Table 6. Specificity Analysis of Proposed and Baseline Models

Iterations / Models Specificity	Lightweight-CNN [9]	DAEN-MaskRCNN [10]	STLF-MOAFDE [Proposed]
10^{th} - Iteration	72.3	73.4	**84.4**
20^{th} - Iteration	74.6	75.8	**86.8**
30^{th} - Iteration	76.9	78.2	**89.2**
40^{th} - Iteration	78.7	80	**91.3**
50^{th} - Iteration	80.5	81.8	**93.2**

3.4 F1-Score

The comparative results of the F1-score of the proposed model are showcased in Table 7, highlighting the balanced harmony between precision and recall over epochs. Unlike baseline models, which overfit the fertilizer classes and underperform on rare nutrient patterns, STLF-MOAFDE maintains a perfect balance in correctly identifying positive and negative fertilizer recommendations in all iterations. The learning rate is increased to avoid misclassifications and false positive rates due to an effective optimization strategy. The results are compared and validated against Lightweight-CNN [9] and DAEN-MaskRCNN [10] over three benchmarked datasets. The model achieves 93.8% F1-Score, which shows the stability and generalization in learning rate, optimization for an effective fertilizer recommendation system.

Table 7. F1-Score Analysis of Proposed and Baseline Models

Iterations / Models F1-Score	Lightweight-CNN [9]	DAEN-MaskRCNN [10]	STLF-MOAFDE [Proposed]
10^{th} - Iteration	71.6	72.5	**83.6**
20^{th} - Iteration	74.2	75	**86.2**
30^{th} - Iteration	76.8	77.5	**88.8**
40^{th} - Iteration	78.5	79.4	**91**
50^{th} - Iteration	80.2	81.3	**93.8**

3.5 Precision

Maximizing the highly reliable fertilizer predictions and minimizing the false positives is measured using precision. Table 8 demonstrates the comparative results of the proposed and existing models from synergic interaction between STLF, CMFL, and AFDE. The data is processed through hierarchical attention layers to prioritize the temporal frames and suppress the redundant signals. The finite features of soil-climate-crop are selected to contribute to the decision boundary. All epochs are reweighted and trained using temporal attention reweighting, which enables the network to detect subtle correlations under fluctuating climatic conditions. By integrating the above mechanisms, the proposed STF-MOAFDE achieves 93.4% precision and confirms its ability to maximize the accuracy and minimize the misclassifications. Additionally, the optimizer recognizes the unsuitable fertilizer options to strengthen the real-time decision-making process.

Table 8. Precision Analysis of Proposed and Baseline Models

Iterations / Models Precision	Lightweight-CNN [9]	DAEN-MaskRCNN [10]	STLF-MOAFDE [Proposed]
10^{th} - Iteration	72.5	73.3	**84.5**
20^{th} - Iteration	75	75.6	**87**
30^{th} - Iteration	77.5	77.9	**89.5**
40^{th} - Iteration	79.5	80	**91.5**
50^{th} - Iteration	81.5	82.1	**93.4**

3.6 AUC-ROC

Receiver operating characteristic (ROC) is an effective quantitative measure of the discriminative capability of the proposed model for all classification thresholds. AUC-ROC measures the trade-off between false-positive rate (FPR) and true-positive rate (TPR), which showcases the model's ability to differentiate between noteworthy and non-noteworthy fertilizer recommendations. In mid-level training, a sharp upward curve is observed on the ROC curve, resulting from higher feature distinctiveness and increased area coverage. In the 50th iteration, the model reached the AUC-ROC value of 0.67, highlighting an ample discriminative power compared to the base Lightweight-CNN [9] and DAEN-MaskRCNN [10] models, which is shown in Table 9. The steady increase over the iterations shows how the model captures nonlinear associations among various combinations of parameters, making it more dependable than the traditional multi-classification frameworks in treating fertilizer recommendation.

Table 9. AUC-ROC Curve Analysis of Proposed and Baseline Models

Iterations / Models AUC-ROC	Lightweight-CNN [9]	DAEN-MaskRCNN [10]	STLF-MOAFDE [Proposed]
10^{th} - Iteration	0.39	0.42	**0.55**
20^{th} - Iteration	0.43	0.44	**0.59**
30^{th} - Iteration	0.47	0.48	**0.63**
40^{th} - Iteration	0.51	0.52	**0.65**
50^{th} - Iteration	0.56	0.55	**0.67**

4 Conclusion

The study introduces a novel hybrid deep learning STLF-MOAFDE model that integrates spatio-temporal learning and bio-inspired optimization to develop smart fertilizer recommendation systems in the dynamic environment of agriculture. The

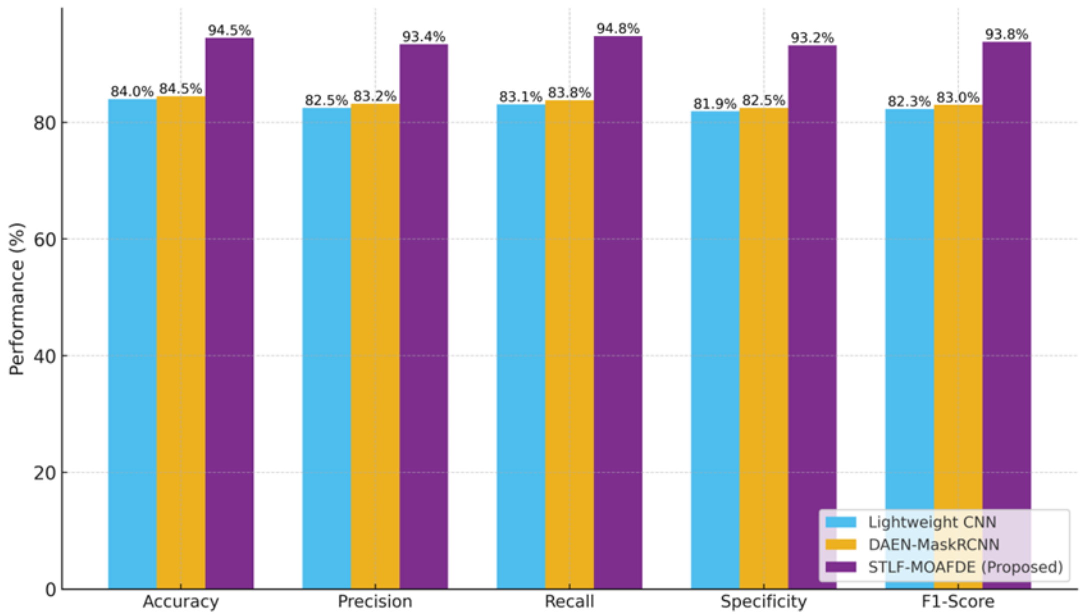

Fig 8. Comparative Results of Proposed and Baseline Models

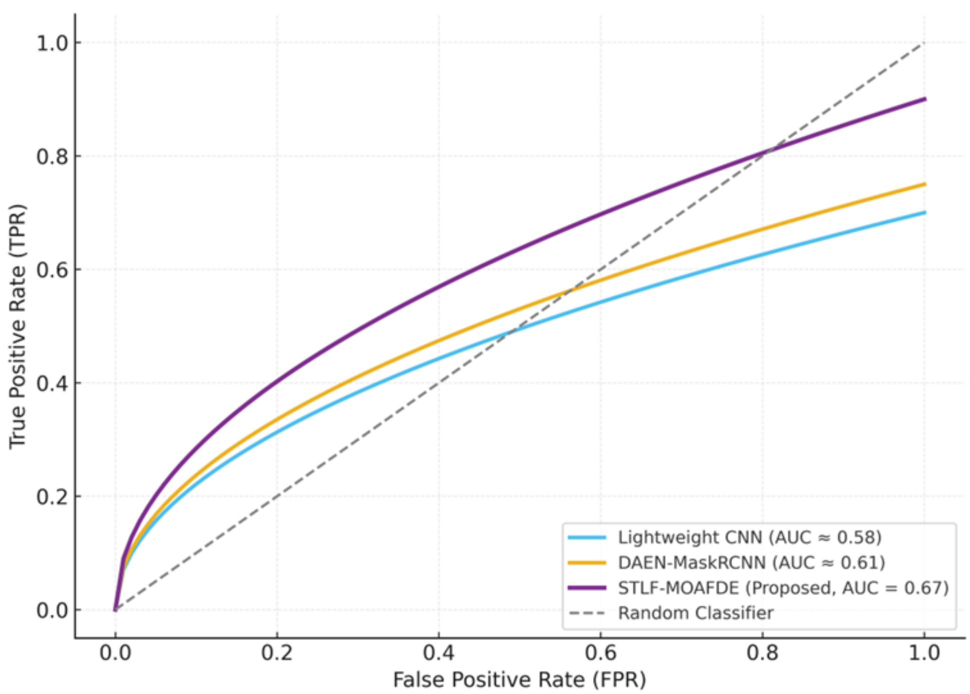

Fig 9. AUC-ROC Analysis of Proposed and Baseline Models

new model captures and optimizes complex relationships, which attain balanced agrarian outputs. Three benchmarked datasets are used (Crop Recommendation, Fertilizer Prediction, and Crop Nutrient Database extracted from Kaggle Repository) to demonstrate the superior predictive accuracy and decision reliability compared to existing Lightweight CNN and DAEN-MaskRCNN models. The model outperforms in all metrics (more than 93%) with an improvement of 4-6% in predictive performance and better stability in temporal learning and optimization efficiency. The results validate that STLF-MOAFDE adaptively responds to changing climatic conditions and reduces fertilizer cost. The new deep learning-based approach bridges the gap between data-driven learning and smart farming, enabling an environment responsible for fertilizer planning to increase crop yield. The proposed model is a promising solution due to its scalability and interpretability, which can be used in large-scale deployment on precision farming platforms.

Though the new model shows adaptability and superior performance, some limitations are that it relies on structured and calibrated datasets, which limit the generalization across unmonitored regions. The computational complexity arises when the data scale increases. Future work will be focused on sensor integration, lightweight deployment architectures, and reinforcement optimization to improve faster decision response and scalability.

5 List of Abbreviations

1. STLF – Spatio Temporal Learning Framework
2. MO-AFDE – Multi Objective Adaptive Firefly Differential Evolution
3. DE – Differential Evolution
4. ML – Machine Learning
5. DL – Deep Learning
6. RP – Reference Points
7. CNN– Convolutional Neural Networks
8. AEN – Auto Encoder Networks
9. ICI – Intelligent Computer Interface
10. CAD – Crop Agricultural Data
11. CND – Crop Nutrient Database
12. FPD – Fertilizer Prediction Data

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