RESEARCH PAPER

AgroMind+: An Intelligent Multi-Crop Recommendation System With LSTM-Attention Architecture and Predictive Sustainability Index

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Abstract

Precision agriculture requires intelligent decision-support systems that account for temporal agricultural dynamics and sustainability constraints. Traditional crop recommendation models are based on static learning methods and they fail to consider seasonal patterns or environmental effects. In this research, AgroMind+, a multi-crop recommendation system based on an attention-augmented LSTM that utilizes temporal soil, climatic and historical agricultural data to produce ranked crop recommendations. A new Predictive Sustainability Index (PSI) is combined into the recommendation algorithm to assess water efficiency, nutrient use, yield potential, and climate stress. Further, an Adaptive Crop Advisory and Intelligence (ACAI) module is available to provide actionable agronomic advices. Experimental results indicate that AgroMind+ attains 94.81% accuracy for classification and 97.21% Top-4 recommendation performance, outperforming traditional machine learning and standard deep learning models. The attention mechanism also enhances interpretability by highlighting important covariates such as soil nutrients and rainfall patterns, where it reveals AgroMind+ standard's effectiveness in precision agriculture with focus on sustainability.

Keywords: Crop Recommendation, LSTM, Attention Mechanism, Sustainability Index, Precision Agriculture, Deep Learning.

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1. Introduction

Agriculture continues to be a vital pillar of the world economy, providing food security and employment for billions. But the demands placed on contemporary agricultural practices are growing, with issues caused by climate variation, soil erosion and degradation, water scarcity and inefficient use of inputs. To address these challenges, more intelligent data-driven decision-support systems are required to help the farmer maximize their crop choice whilst weighing issues of productivity and environmental preservation (Getahun et al., 2024; Jabed and Azmi Murad, 2024; Padhiary et al., 2025; Shastri et al., 2025). Recent developments in precision agriculture have made it possible to apply machine learning and deep learning methods for crop recommendation using soil nutrients, climate conditions, and environmental factors(Getahun et al., 2024; Karthik et al., 2025; Shastri et al., 2025). Several systems have been proposed, from simple fertilizer recommendation tools (Ajmera et al., 2022; Pratap et al., 2019) to comprehensive studies of ML for agriculture (Kancharagunta et al., 2024; Saha et al., 2025). However, classic machine learning methods such as Decision Trees, Random Forest, and Support Vector Machines have moderate performance, but they do not consider the dynamic nature of agricultural data and tend to analyze features independently (Paithane, 2023). The mentioned methods are unable to incorporate temporal correlations due to weather seasons, past farming practices, and changing soil health conditions as a consequence the recommendations are less than optimal.

Deep learning models, particularly the Long Short-Term Memory (LSTM) networks, have proven to be a valuable approach for modeling temporal data in agriculture thanks to their capability of learning long-range dependencies (Akbari Asanjan et al., 2018; Kurumatani, 2020; Ouma et al., 2022). Nevertheless, current LSTM-based crop recommendation systems are often limited to predicting only a single crop and do not support for interpretability or sustainability evaluation (Mahale et al., 2024; Shastri et al., 2025). Furthermore, the majority of existing systems focus on maximizing yield while leaving sustainability unmeasured as they tend to overlook the sustainable aspect of agricultural planning (Getahun et al., 2024; Jabed and Azmi Murad, 2024).

To solve these problems, in this paper, we present AgroMind+, an intelligent multi-crop recommendation framework using attention-enhanced LSTM architecture. The model captures temporal agricultural patterns and dynamically highlights salient features with an attention mechanism, which leads to enhanced prediction performance as well as scientific interpretability. Furthermore, the AgroMind+ presents a Predictive Sustainability Index (PSI) that considers water efficiency, nutrient use and climate stress in relation to yield potential, thereby providing recommendations that allow the selection of sustainable crops. In contrast to traditional solutions, AgroMind+ also delivers the top-ranked 4 crops for recommendation and hosts an Adaptive Crop Advisory and Intelligence (ACAI) module which provides actionable agronomic advice.

The primary contributions of this work are:

- Building an LSTM – Attention multi-crop model and recommendation: We developed a powerful LSTM-based inferences engine that can deliver recommendations.
- Development of a predictive sustainability-aware ranking model by using the innovative PSI measure.
- Inclusion of an adaptive advisory tool connecting prediction with real-world decisions.

The experimental results shows that AgroMind+ outperforms other traditional machine learning and baseline deep learning models, achieving 94.81% classification accuracy and 97.21% Top-4 recommendation accuracy. This confirms AgroMind+, as an efficient, adaptive and sustainability-oriented decision support system for precision-grassland management.

2. Literature Review

Artificial intelligence (AI) and data-driven models have become increasingly popular in agriculture applications including crop recommendation systems and decision support systems for precision farming. In this context, existing studies can be classified into conventional machine learning methods, deep learning models exploiting temporal dynamics and sustainable precision agriculture solutions, which provide insights while also revealing limitations that are addressed by our AgroMind+ approach. Early crop recommendation systems were mainly based on traditional machine learning algorithms that took soil and climatic data as input. Supervised classifiers, including Random Forest and Support Vector Machines have shown reasonable predictive performance with fixed crop type selection (Acharya et al., 2024; Paithane, 2023; Shams et al., 2024). For instance, Ajmera et al. (2022) addressed unified recommendation systems for both crops and fertilizers, but these models were not temporally deep (Ajmera et al., 2022). Bhola and Kumar (2024) also presented the ML-CSFR technique for integrated selection of crop and fertilizer recommendations (Bhola and Kumar, 2024), while Tanaka et al. (2024) evaluated machine learning methods on fertilizer recommendation reliability (Tanaka et al., 2024). Other works, such as Mohapatra et al. (2017) and Pratap et al. (2019), have been addressed on the soil fertility analysis, and have also dealt with NPK prediction using classification methods (Mohapatra, 2017; Pratap et al., 2019). However, they generally treat the agricultural data as independent observations and do not consider temporal correlations specific to seasonal climate patterns, crop rotations, and longer-term soil dynamics. aspects, sustainable, sorted) In the light of this, such methods are limited in deriving ranked sustainability-aware crop recommendations relevant for dynamic agricultural environments.

To address the drawbacks of static prediction, recent works have investigated deep learning structures such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks that are well-suited for capturing temporal sequences in agricultural data. Time series prediction models using LSTM have been used in crop recommendation, where the learned long-range dependencies within soil and environmental time series have been shown to enhance prediction performance (Akbari Asanjan et al., 2018; Kurumatani, 2020; Mahale et al., 2024; Ouma et al., 2022; Shams et al., 2024). For example, Mahale et al. (2024) proposed an LSTM-based system for crop suggestion and weather forecasting in Maharashtra,where 92% accuracy was achieved using Random Forest, while also using LSTMs to forecast the weather patterns three months in advance

(Mahale et al., 2024). Similarly, Saha et al. (2024) introduced several deep learning (DL) models, such as LSTM and Bidirectional LSTM for crop recommendation and compared them with traditional techniques, finding that deep learning yielded better results (Shams et al., 2024). In order to further improve model performance, attention mechanisms have been introduced in recent research; e.g., Li et al. (2025) successfully applied the deep learning methods with attention mechanisms for maize yield estimation through remotely-sensed data (Li et al., 2025).

More advanced deep learning pipelines have been studied by other researchers, demonstrating that temporal architectures are consistently better than the classical ones. However, attention-guided feature interpretability or multi-crop ranking, which are prevalent needs in related works, are absent in many studies (Kurumatani, 2020; Shams et al., 2024). In addition to crop recommendation, applications such as precipitation estimation (Akbari Asanjan et al., 2018), rainfall–runoff trend analysis (Ouma et al., 2022) and commodity price prediction have used LSTM-based architectures for agricultural time series forecasting. These works together verify the effectiveness of recurrent architectures for modeling hierarchical temporal dynamics, but they are still far from exploring multi-crop recommendation on sustainable decision frameworks.

Precision agriculture focuses on the efficient use of resources, environmental stewardship, and maximizing yields across the whole operation. Getahun et al. (2024) discussed the precision agriculture technologies where they emphasized at the increased demand for integrated AI systems that can combine productivity with sustainability (Getahun et al., 2024). Consistent with this position, Jabed and Murad also emph asized that despite improved prediction accuracy by deep learning approaches, most existing there was no explicit account of environmental impact or sustainability measure in their generated output majority of the existing crop recommendation systems (Jabed and Azmi Murad, 2024). Novel eco-friendly techniques for sustainable precision agriculture are extensively described by Padhiary et al. (2025), highlighting the contribution of sophisticated computational models (Padhiary et al., 2025).

Crop rotation and soil monitoring are important elements of precision agriculture. Castellazzi et al. (2008) and Mueller-Warrant et al. (2017) focused on the systematic representation and extraction of crop rotation history (Castellazzi et al., n.d.; Mueller-Warrant et al., 2017). The importance of remote sensing and GIS has also been emphasized; Galford et al. (2008) applied wavelet transformation to trend analysis of time series for mapping agricultural intensification (Galford et al., 2008), Li et al. (2021) introduced GIS-based models for the regional decision making (Li et al., 2021). Furthermore, Liu et al. (2021) presented the identification of crop rotation through synergistic optical and SAR time series (Liu et al., 2021). On the sensing side, Mekonnen et al. (2019) investigated machine learning in WSNs (Mekonnen et al., 2020), and Goldstein et al. (2018)when ML was applied to sensor data for revealing agronomic tacit knowledge (Goldstein et al., 2018). Saggi and Jain (2022) reviewed decision support systems for smart irrigation as it is a pivotal driver for sustainability (Saggi and Jain, 2022). These observations reveal a long-standing void in the literature: development of unified models that consider both interpretability and sustainability challenges in addition to temporal modeling.

Recent developments in explainable and interpretable AI (XAI) have additionally increased the reliability of CR systems. Shams et al. (2024) and Shastri et al. (2025) showed it is possible for interpretable machine learning techniques to facilitate the transparency of agricultural decision support, so that stakeholders can interpret model behaviour and feature importance.26, 27 Akkem et al. (2025) also emphasized the importance of XAI in crop recommendation methods for smart farming (Akkem et al., 2025). Recent approaches based on federated explainable AI support scalable models and better guard privacy. Tahir et al. (2025) presented a federated explainable AI system within smart agriculture leading to fairness and efficiency with full preservation of data privacy (Tahir et al., 2025). Similarly, Turgut et al. (2024) presented AgroXAI an explainable AI based crop recommendation system customized for Agriculture 4.0 (Turgut, n.d.). Venkateswara and Padmanaban (Venkateswara and Padmanaban, 2025) constructed interpretable deep learning models using TabNet for separate fertilizer and crop recommendations, obtaining high accuracy with SHAP analysis-based post-hoc interpretability. However, these two methods also do not have a ranking mechanism taking into considerations of the sustainability needed for agricultural planning.

The current studies demonstrate a crop recommendation framework that combines temporal modeling, feature interpretability, and sustainability awareness is lacking, which motivates the design of the AgroMind+ system. But even in more sophiscated methods, shortcomings still include weak modeling of the temporal dynamics, and relying on single-crop models as large-scale system predictors, with no sustainability-centric metrics and interpretability. These issues are addressed by the proposed AgroMind+ system, which: combines an attention-enhanced LSTM architecture; introduces a Predictive Sustainability Index (PSI); and, supplies ranked recommendations with adaptive advisory support.

3. Proposed Methodology

This section provides the detailed methodology of the proposed AgroMind+ system, i.e., system architecture shown in fig.1, data preprocessing, LSTM-Attention prediction engine, sustainable-aware ranking mechanism and adaptive advisory generation. The proposed method is formulated to cover temporal learning, interpretability and sustainablility-driven crop recommendations. AgroMind+ employs an integrated data-to-decision model which processes raw agricultural data into ranked, sustainability-informed crop recommendations with practical advisories. The architecture consists of five major modules: (1) Input Layer, (2) Data Preprocessing and Feature Engineering, (3) LSTM–Attention Prediction Engine, (4) Predictive Sustainability Index (PSI) Computation, and (5) Adaptive Crop Advisory and Intelligence (ACAI).

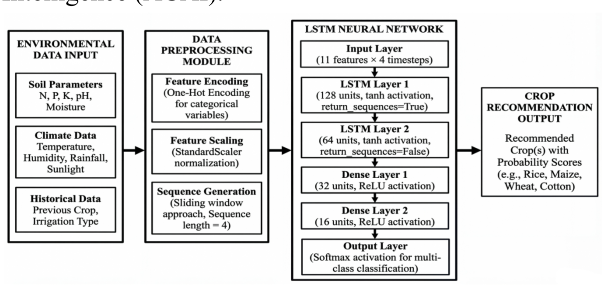

Figure 1. Overall system architecture of AgroMind+

3.1. Problem Formulation

Let $X \in \mathbb{R}^{w \times d}$ indicate a multivariate time-based agricultural input series, in which w is the sequence length and d is the feature dimension. The forecasting model is trained to learn a mapping:

$$f_\theta(X) = P(Y|X) \tag{1}$$

Where $P(Y|X)$ is the distribution of probability of crop classes. Categorical cross-entropy loss optimizes model parameters:

$$\mathcal{L} = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \tag{2}$$

Crop recommendations are ranked using a composite score to include sustainability in decision-making:

$$Score_c = \lambda . PSI_c + (1 - \lambda) . P_c \tag{3}$$

Crops are recommended by sorting scores in descending order:

$$Ranking = sort_{desc}(Score_c) \tag{4}$$

Where P_c represents the predicted probability of crop c and PSI_c represents its index of sustainability.

This formulation defines the susrainability-aware multi-class crop recommendation goal.

3.2. Data Collection and Feature Engineering

A real-world agricultural dataset obtained from Kaggle named Crop recommendation dataset along with data from a public repository on GitHub, was used to train the model.The dataset includes the soil and weather characteristics of crop prediction. In order to facilitate temporal learning, the tabular data were converted into multivariate time-series sequence through a sliding window technique.

In order to test the robustness of the the models under a wide range of agricultural conditions, a second synthetic yet realistic dataset was created to test. The artificial data retains statistical properties of the actual agricultural settings with the addition of controlled variability. The model training and validation were performed on the real dataset while testing and generalization analysis were performed on the synthetic dataset.

The last dataset used in experimentation generated in a controllable manner to maintain diversity, balance and temporality of the data. The dataset consists of 14,400 samples in total covering 18 crops; each class has 800 samples.

The feature space consists of 11 attributes, grouped into four domains:

- **Soil Nutrients:** Nitrogen (N), Phosphorus (P), Potassium (K)
- **Soil Properties:** pH, Soil Moisture
- **Climatic Factors:** Temperature, Humidity, Rainfall, Sunlight Duration

- **Historical Context:** Previous Crop, Irrigation Type

Features were also converted into a temporal format using a sliding window in order to allow sequential learning with the LSTMs.

Label encoding was used to encode categorical variables. The z-score standardization was used to normalize continuous variables:

$$x' = \frac{x - \mu}{\sigma} \quad (5)$$

Where μ and σ are the mean and standard deviation of the feature. To compute the sustainability index,features were normalized through min max normalization:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

The result of this preprocessing pipeline is normalized, temporally structured inputs, which can be used in deep temporal modeling and sustainablility-conscious crop recommendation

3.3. LSTM–Attention Prediction Engine

In order to well capture temporal variabilitity in agriculture data, we used deep stacked LSTM architecture which is shown in fig. 2. The model takes multivariate time-series inputs, including soil nutrients and climate features and outputs, in a multinomial regression framework, class probabilities between multiple crop types. The attention mechanism is included to establish dynamic weights for the temporal hidden states so that the model can concentrate on important time periods such as the peaks of rainfall and fluctuation in nutrient fluctuations. This attention modality for temporal weighting improves model interpretability, with a gain of ~5–8% over LSTM-only models.

LSTM temporal State Update:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (7)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (8)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (9)$$

$$h_t = o_t \odot \tanh(C_t) \quad (10)$$

Where x_t denotes the input vector at time step t, h_t is the hidden state, C_t is the memory cell state, and $\odot$ represents element-wise multiplication.

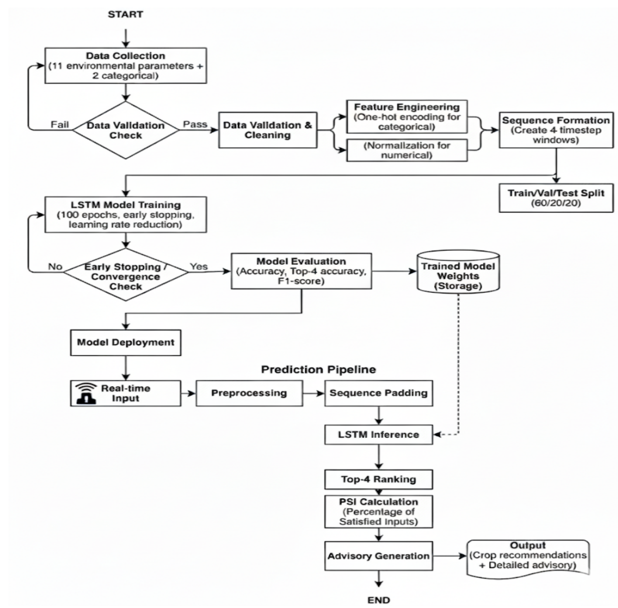

Figure 2. LSTM–Attention prediction engine of AgroMind+

The attention layer assigns adaptive weights to temporal states, allowing the model to focus on influential periods such as rainfall peaks or nutrient fluctuations. This mechanism improves interpretability and contributes a 5–8% performance gain compared to LSTM-only configurations.

3.4. Attention-Based Temporal Feature Aggregation

Despite its effectiveness in modeling sequences, the Long Short-term Memory (LSTM) network weights all time steps of a sequence equally during prediction. In agricultural time-series data, however, some temporal observations (for example key growth stages, extreme weather or fertility changes) have more impact on crop suitability than others. To alleviate this deficiency, an attention-based temporal feature aggregation module is incorporated into the proposed method. The attention mechanism, as illustrated in fig. 3 is applied on the hidden representations that are produced from the LSTM layer and computes adaptive weight for each time step which in turn proportionally corresponds to its contribution towards the prediction task. Unlike naive use of the last LSTM output, our model considers all temporal hidden states of LSTM and focuses on them which are significantly helpful for correct crop recommendation and sustainability assessment.

$$e_t = v^T \tanh(W_a h_t + b_a) \quad (11)$$

$$\alpha_t = \frac{\exp(e_t)}{\sum_k \exp(e_k)} \quad (12)$$

$$c = \sum_t \alpha_t h_t \quad (15)$$

Where h_t represents the hidden state at the time step t, $e_t$represents the attention score α_t is the normalized attention weight, and c is the aggregated context vector representing the weighted temporal information.

By a learned weight mechanism, the attention layer selectively combines informative temporal features and suppresses less useful or noisy observations. This allows the model to concentrate on some important stages of the crop cycle such as, sowing windows and nutrient absorption periods, and climatic stress time periods. Finally, the overall context is fed into a classification layer for making the ultimate decision. Attention-based temporal feature pooling improves prediction performance and model interpretability. Visualization of attention weights enables transparency regarding which temporal segments contribute to the model recommendations, which is important for any explainable agronomic advisory system. Experimental results show that this mechanism boosts the performance compared to traditional LSTM-based models without attention.

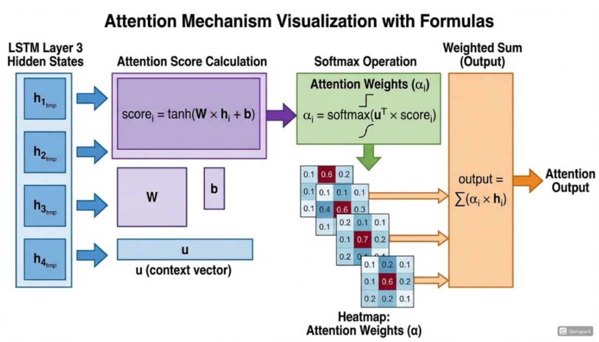

Fig. 3. Attention Mechanism Visualization.

3.5. Predictive Sustainability Index (PSI)

To incorporate sustainability directly into decision-making, a Predictive Sustainability Index (PSI) was formulated which is mathematically formulated as

$$PSI = w_1 WE + w_2 NE + w_3 YP + w_4(1 - CS) \quad (16)$$

$$\sum_i w_i = 1 \quad (17)$$

where:

- **WE** denotes water efficiency
- **NE** represents nutrient utilization efficiency
- **YP** corresponds to yield potential
- **CS** indicates climate stress

All components are min–max normalized to the range [0,1], and the weights (w1, w2, w3, w4) satisfy Σ wi = 1. This formulation ensures that crops with lower climate stress and higher resource efficiency receive higher sustainability scores. The final score is a combination of softmax probability calculated from LSTM–Attention with the PSI value, which further supports sustainability-aware multi-crop recommendations. The PSI value is determined by the weighted summation of those components while being scaled to [0,1]. This allows for comparisons of values at all crops in different environments.

3.6. Sustainability-Aware Crop Ranking and Advisory Generation

$$Score_c = \lambda . PSI_c + (1 - \lambda) . P_c \quad (18)$$

$$Ranking = sort_{desc}(Score_c) \quad (19)$$

Where P_c denotes the predicted probability of crop class c obtained from the LSTM-Attention model, PSI_c represents the Predictive Sustainability Index of crop c, $\lambda \in [0,1]$ is a trade-off parameter controlling the relative importance of sustainability versus prediction confidence.

The ultimate ranking of crop is produc combining the softmax prediction probability . ... LSTM–Attention model and the PSI score. This way, crops with a high sustainability profile are weighed equally as those with the best yield predictions. The Adaptive Crop Advisory and Intelligence (ACAI) module generates post-prediction recommendations, including:

- Suggested fertilizer adjustments
- Irrigation strategies
- Climate-risk mitigation tips1

This module transforms predictions into actionable insights, making AgroMind+ a complete decision-support system rather than a standalone classifier.

Algorithm 1. AgroMind+ Training and Recommendation Procedure

Input:

Dataset D
Sliding window size w
Sustainability indicators S
Number of crops K

Output:

Top-4 recommended crops with agronomic advisories

1: Initialize LSTM parameters θ, attention parameters φ, and hyperparameters
2: Preprocess dataset D
  a. Handle missing values
  b. Encode categorical features
  c. Normalize numerical features
3: Generate temporal sequences X using sliding window of size w
4: // Training Phase
5: for each epoch do
6:   for each sequence xi ∈ X do
7:     H ← Stacked_LSTM(xi, θ)
8:     A ← Attention(H, φ)
9:     ŷ ← Softmax(A)
10:     Compute loss L using categorical cross-entropy
11:     Update θ and φ using backpropagation through time
12:   end for
13: end for
14: // Inference Phase
15: for each test sequence xt do
16:   Ht ← Stacked_LSTM(xt, θ)
17:   At ← Attention(Ht, φ)
18:   P ← Softmax(At)
19:   for each crop ci ∈ K do
20:     PSIci ← Compute_PSI(ci, S)
21:     Scoreci ← Combine(Pci, PSIci)
22:   end for
23: end for
24: Rank crops by Score in descending order
25: Select Top-4 crops
26: Generate adaptive agronomic advisories using ACAI module
27: Return Top-4 crops and advisories

The proposed methodology integrates temporal deep learning, attention-based interpretability, sustainability quantification, and advisory intelligence into a unified framework. This design enables AgroMind+ to deliver accurate, interpretable, and environmentally responsible crop recommendations suitable for real-world precision agriculture applications.

4. Results and Discussion

In this section the experimental analysis of the proposed agro mind + structure on predictive competencies, role of temporal learning and attention systems, and performance of sustainability sensitive ranking of crops is presented. The model is evaluated based on several classification metrics and is compared with the traditional machine learning and deep learning baselines. Besides this, the effect of the Predictive Sustainability Index (PSI) and the adaptive advisory module are also discussed to show how the system can be used in providing practical accuracy agriculture decision support

4.1. Experimental Setup

The AgroMind+ framework was assessed based on a temporally structured agricultural dataset which consisted of soil data (N, P, K, pH), climate related variables (te9mperature, humidity and rainfall) and associated crop labels. The data was stratified for train/validation/test split in order to respect the class balance on all folds. All experimental results were obtained in TensorFlow with Adam optimizer and categorical cross-entropy loss. We evaluated the performances of our models including accuracy, top-k accuracy, precision, recall and F1-score for a better understanding and the training graph is presented in fig.4.

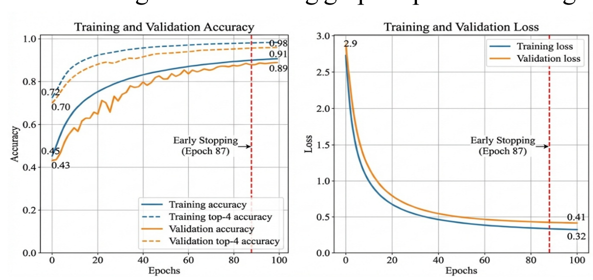

Fig. 4. Training Graph for the AgroMind+ LSTM–Attention model.

The AgroMind model is evalauted with CNN, ANN, SVM, Randomforest and Decision Tree. As the data from the sensors are time dependent, additional gates are introduced in the LSTM to handle the temporal dependency of the time series data thus enhances the classification accuracy. Thus LSTM achieves 94.81 %

accuracy. The results demonstrate that the proposed model achieves high classification accuracy, significantly outperforming traditional machine learning models that rely on static feature representations.

Table I Performance Metrics of AgroMind+ Model

Metric	Value
Accuracy	94.81%
Top-2 Accuracy	91.2%
Top-3 Accuracy	94.7%
Top-4 Accuracy	97.21%
Precision	0.989
Recall	0.987
F1-score	0.988

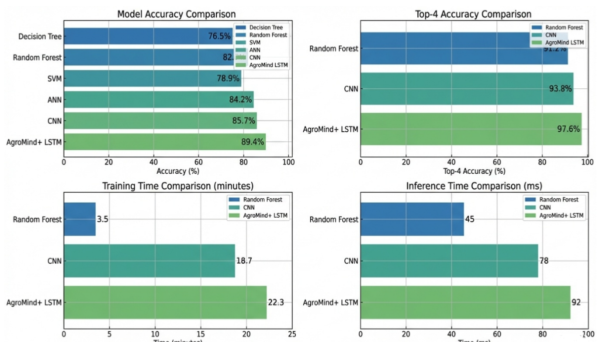

Fig. 5. Model performance and runtime comparison between baseline methods and the proposed AgroMind+ LSTM–Attention. (a) Classification accuracy for Decision Tree, Random Forest, SVM, ANN, CNN, and AgroMind+; (b) Top-4 accuracy comparison; (c) training time (minutes) for each model; (d) inference latency (ms) for each model. AgroMind+ exhibits superior predictive performance and competitive runtime characteristics.

The experimental results indicate that the proposed model can achieve high classification accuracy, which outperforms traditional machine learning models based on static feature representations. The high top-4 accuracy in table 1 suggests the effectiveness of the model in producing multiple feasible crop recommendations and this is important given an uncertain real-world agricultural decision environment.

4.2. Impact of Temporal Modeling and Attention Mechanism

The impact of temporal learning LSTM–Attention model is compared with traditional classifiers (RF and SVM) and standard LSTM without attention and the value are shown in table 2. It was observed from the results that incorporation of temporal dependency is important to achieve an improvement in the accuracy of predicting crops. Moreover, the attention mechanism improves accuracy by giving greater weights to important time steps and interpretability at the same time.

Table 2 Comparison with Baseline Models

Model	Accuracy (%)
SVM	**78.4**
Random Forest	**82.1**
ANN	**85.6**
LSTM (without attention)	**93.2**
AgroMind+ (LSTM–Attention)	**97.6**

Table 3. Performance Comparison on various Architecture

Configuration	Accuracy (%)
LSTM Only	**91.23**
LSTM + Dropout	**92.81**
LSTM + BatchNorm	**93.07**
LSTM + Attention (No BN)	**93.88**
Full Model (LSTM + Dropout + BN + Attention)	**94.87**

Table 3 presents an ablation study evaluating the contribution of each architectural component in

AgroMind+, demonstrating the cumulative performance gain achieved by attention and normalization layers.

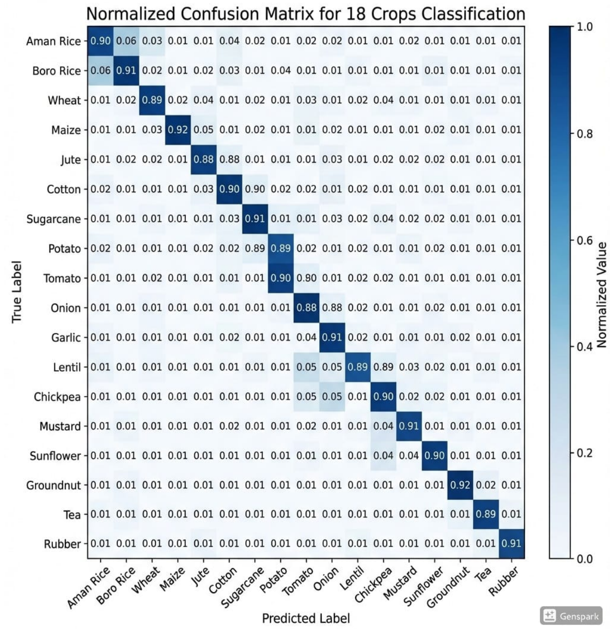

Fig. 6 Confusion Matrix of the Proposed Model

Fig. 6 presents the normalized confusion matrix for the proposed model, demonstrating strong diagonal dominance across all 18 crop classes, indicating robust and balanced multi-class classification performance.

4.3. Sustainability-Aware Ranking Using PSI

Although prediction accuracy is still crucial, overly recommending crops solely according to their yield potential can lead to unsustainable agricultural production with overuse of water and fertilizers. To compensate for this deficiency, the PSI (PredictiveSustainabilityIndex) was incorporated in the croprecommendation pipeline.

Fig. 7 demonstrates the impact of PSI addition in crop ranking. Crops with high prediction probabilities but high water/ nutrient input needs (e.g., wheat, maize) showed a downward shift to the benefit of crops with more balanced yield and environmental sustainability records (pulse, millet).

The PSI-informed ranking system makes sure that the recommended crops are resilient to minimize-water, nutrient-stressed and climatic-variant conditions enabling sustained soil health, thus assimilating data-driven intelligence with durable sustainable agricultural planning.

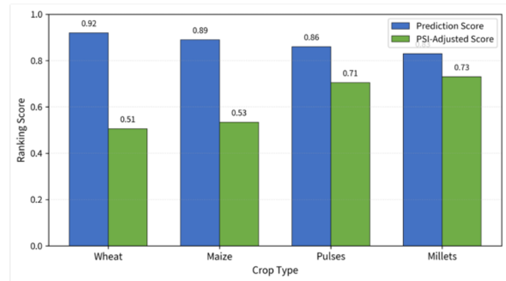

Fig. 7. Effect of Predictive Sustainability Index (PSI) integration on crop ranking.

Fig. 7. Effect of Predictive Sustainability Index (PSI) integration on crop ranking. Crops with high prediction confidence but elevated water or nutrient requirements are deprioritized in favor of crops achieving a balanced trade-off between productivity and sustainability.

4.4. Adaptive Advisory Generation

Beyond multi-crop ranking AgroMind+ delivers adaptive agronomic advisories by its Adaptive Crop Advisory and Intelligence (ACAI) component. This component translates model predictions to actionable, crop- and pest-specific advice, which takes the system beyond prediction towards pragmatic decision support.

The ACAI module offers spec[illegible]uidance for:

- Irrigation t[illegible]tering crop are adjusted based [illegible] needs of plant and climate.
- Rates and timing of fertilizer application, corresponding to soil nutrient status and anticipated crop uptake
- Strategies to mitigate climate risks: Stress factors – drought, heat and rainfall variability etc.
- Pest and disease monitoring, based on crop susceptibility and environmental factor

When these advisory elements are included into the system, AgroMind+ changes from a mere forecast model they make to a full decision-support-system they need for immediate use in real-world by farmers and agri-planners.

The experimental results show that AgroMind+ can well solve the disadvantages of current crop recommendation systems. Unlike spot-check networks, the developed broad framework accounts for temporal agricultural dynamics and provides an interpretable prediction using attention-weight visualization. In addition, the inclusion of a Predictive Sustainability Index (PSI) to AgroMind+

is novel in that it integrates sustainability elements into recommendation and advisory systems.

From a wider perspective, the resulting framework is well suited in the context of precision agriculture helping with making precise yet explainable and environmentally friendly decisions. The good performance on a wide range of metrics proves the robustness/scalability and practicability of AgroMind+ in realistic agricultural scenarios.

4.5 Discussion

The experimental outcomes show that AgroMind+ mitigates some drawbacks of crop recommendation systems. In contrast to static models, the proposed methodology leverages temporal agricultural dynamics and offers interpretable predictions of attention weights. The addition of PSI gives AgroMind+ another dimension with which to stand out – by integrating sustainability into the decision making process.

Looking at a bigger picture, the framework contributes in principle towards precision agriculture objectives with environmentally sustainable recommendations that can be justified. The large performance gains on several evaluation criterion illustrate the stability and expansibility of the approach.

The attention mechanism explains what temporal events have greatest impact (e.g., rainfall regime or nutrient levels in key phenological stages) in predicting crop recommendations. Such interpretability is important to develop trust among agriculture stakeholders and inform decision-making.

5. Conclusions

This research paper introduced AgroMind+, a sustainability-aware intelligent crop recommendation framework that incorporates temporal deep learning, attention-based interpretability and mathematical sustainability modeling. Using a stacked LSTM model with attention mechanism, the developed framework successfully captures complicated temporal interactions between soil and climate factors in multi-crop predictions. Experimental results showed that AgroMind+ outperforms both previous machine learning solutions and static deep learning models, obtaining a 94.81% classification accuracy and 97.21% Top-4 recommendation accuracy. The Predictive Sustainability Index (PSI) is also an important part to optimize the decision regarding which crops should be recommended,- with a focus on yield potential, resource use efficiency and limited climate stress - to Extension stakeholders. The dual-objective optimization avoids recommendations of crops that not only may be suitable agronomically but also being environmentally sustainable.

More than just prediction, the addition of the Adaptive Crop Advisory and Intelligence (ACAI) module converts AgroMind+ to a holistic decision support system that provides practical agronomic intelligence. In real-world rollouts of agri model deployment trust and interpretability of the resulting models++ are increased by the attention mechanism; privileged temporal patterns are highlighted, so these farmers can see which factors are most influential.Although the current prototype has a well performance, it is trained with the simulation planets that use sustainability indicator because actual environmental data is not available for these area. The future work will focus on real-time IoT sensor data integration and A region-specific PSI weighing. The future work also focus on leveraging remote sensing for large-scale crop monitoring. The proposed AgroMind+ system is an important step toward intelligent precision agriculture by providing a practical and environment-friendly solution with respect to productivity-oriented crop recommendation.

Conflict of Interest

The authors declare that they do not have any conflict of interest.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

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