International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(18s) 2026 pp. 1359-1378
https://doi.org/10.70917/ijcisim-2026-4983
Article

An Explainable Hybrid Attention Based TabNet–BiLSTM Framework for Intelligent Soil Data-Driven Crop and Fertilizer Recommendation

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Abstract: Accurate crop selection and fertilizer recommendation based on soil laboratory data analysis are essential for sustainable agriculture and precision nutrient management. Most existing crop recommendation systems lean on standalone machine learning or deep learning architectures that constrain their ability to model sparse feature relevance and contextual nutrient interactions simultaneously while keeping the model interpretable. We propose AgriDeepFusion-XAI, a hybrid deep learning architecture introduces a dual branch attention sequence fusion mechanism. It combines TabNet based sparse feature selection with BiLSTM based contextual representation learning then layers on explainable decision analysis through SHAP and LIME for intelligent crop classification and fertilizer recommendation. The TabNet branch carries out sequential attentive feature selection using sparsemax-based masking to identify the important soil attributes, while the BiLSTM branch learns the bidirectional dependencies hiding in soil feature sequences. Embeddings from both branches are fused through a dense integration layer to perform multi-class crop prediction which is followed by a rule guided fertilizer recommendation module. SHAP and LIME explainability techniques are integrated to enhance the interpretability which helps to provide global feature importance and instance-level explanations. The proposed architecture was evaluated using a seven years soil laboratory dataset collected from soil lab located in Madurai, Tamilnadu, India. It includes sixteen physiochemical soil attributes and twenty two crop categories. Data preprocessing pipeline included missing values handling, feature normalization, categorical encoding and stratified data partitioning. Model performance was evaluated through stratified five fold cross validation. Experimental results shows that AgriDeepFusion-XAI achieves 97.3% classification accuracy, 97.92% macro-F1 score, and 97.85% precision and 97% recall which outperforms standalone TabNet and BiLSTM models by 3-4%. The proposed AgriDeepFusion-XAI architecture provides a scalable, explainable, and reliable decision support system for an intelligent smart agricultural system.
Keywords: BiLSTM, crop prediction, deep learning for agri soil data analytics, explainable artificial intelligence, fertilizer recommendation, hybrid deep learning, LIME, precision agriculture, SHAP, tabnet

1. Introduction

Agriculture is being reshaped by rapid advances in Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and precision farming technologies. Rising global food demand coupled with climate variability, soil degradation, and resource constraints need intelligent decision-support systems that capable of improving productivity without sacrificing sustainability. Precision agriculture harnesses data driven technologies to fine tune crop management practices through accurate analysis of soil, climate, and environmental conditions. Recent reviews confirm that AI based agricultural systems significantly improve crop selection, soil fertility assessment, yield prediction and nutrient management [3] [4].

Among the various factors that drive agricultural productivity, soil health remains one of the most decisive in determining crop suitability and fertilizer requirements. Modern soil labs now produce large volumes of structured tabular data comprises physicochemical parameters such as pH, nitrogen (N), phosphorus (P), potassium (K), organic carbon (OC), and electrical conductivity (EC). These attributes offer valuable insights into soil fertility status [26]. Transforming this heterogeneous soil attributes into actionable crop and fertilizer recommendations remains challenging because of the

complex nonlinear interactions among soil properties. Recent advances in deep learning have shown strong promise in handling high-dimensional agricultural datasets for prediction and classification tasks [1] [5].

Machine learning based crop recommendation systems built on Random Forest, Support Vector Machine, Gradient Boosting and XGBoost have been widely adopted for crop recommendation and soil classification. Although these methods have delivered promising results in improving yield and nutrient management, they requires extensive feature engineering and often fall short in capturing higher order feature interactions [23] [25]. On the other hand, Deep learning architectures have shown superior representational power across various agricultural applications ranging from crop classification and yield forecasting to disease diagnosis and nutrient prediction. Recent reviews resulted that deep learning models outperform traditional machine learning approaches whenever large scale agricultural datasets are available [6] [28].

Deep learning for structured tabular agricultural data is still challenging research area because of soil datasets differ fundamentally from image and time series data. TabNet has emerged as an effective deep learning architecture for tabular data because of its learning through sequential attention mechanisms and sparse feature selection. It improves both prediction performance and model interpretability by dynamically selecting the most informative features for each decision step. However, these benefits may not be sufficient for capturing the complex relationships between soil nutrients that collectively impact crop suitability and fertilizer recommendations. Recent studies on crop recommendation systems have highlighted the necessity of hybrid architectures that combine feature selection, contextual representation learning and explainability in a single framework for more accurate and transparent decision making processes [7] [22].

Soil attributes are not temporal in nature, whereas agronomic variables are strongly contextual dependent. Soil pH directly affects phosphorous availability and organic carbon affects nitrogen retention and nutrient mobility. One way to model these relationships is to learn the interactions among features rather than assuming independence among them. Bidirectional Long Short-Term Memory (BiLSTM) networks offer an efficient way of capturing contextual relations through forward and backward dependency learning. When applied to structured agricultural data represented in the form of feature sequences, BiLSTM can output enriched latent representations that nicely complement the sparse attention capabilities of TabNet.[13].

Transparency has become a non negotiable requirement for agricultural AI systems in addition to achieve strong predictive performance. Stakeholders including farmers, agronomists, and policymakers increasingly prefer AI based recommendations that provide clear and understandable reasoning before incorporating them into decision-making processes. SHAP and LIME are powerful Explainable Artificial Intelligence (XAI) techniques to interpret the outputs of complex machine learning and deep learning models [10]. Recent research show that integrating explainability into crop recommendation systems improves user confidence, promotes transparency, and encourages wider adoption by clearly demonstrating the influence of individual soil properties on prediction results [1] [2] [6].

Despite the substantial progress in agricultural AI, three major research gaps persist (i) existing crop recommendation systems rarely integrate attention based tabular learning with contextual sequence modeling in one architecture. (ii) many high performing models continue to operate as black box systems with limited interpretability. (iii) few studies combine predictive modeling, fertilizer advisory mechanisms, and explainability within a deployment oriented agricultural decision support framework. To address these gaps, we introduce AgriDeepFusion-XAI, an explainable hybrid attention based TabNet-BiLSTM architecture that unifies sparse feature attention, contextual nutrient interaction learning, fertilizer recommendation, and explainable artificial intelligence into a single intelligent agricultural decision support system [22].

The rest of this paper is organized as follows. Section 2 surveys recent literature in smart agriculture, deep learning for tabular data, and explainable AI. The proposed AgriDeepFusion-XAI framework and methodology is presented in Section 3. Section 4 describes the experimental setup, dataset description, evaluation metrics and ablation study. Section 5 presents the experimental results and the comparative analysis. Finally, Section 6 wraps up the points for future research directions.

2. Literature Survey

Artificial Intelligence has become a disruptive force in modern agriculture to support informed decision making in areas such as crop management, soil fertility analysis, irrigation planning, and fertilizer recommendation. The rapid growth of agricultural data availability and the advances in machine learning and deep learning have increased the development of the data driven approaches for precision farming. Recent studies demonstrated that AI-assisted agricultural systems Recent studies indicate that AI-assisted agricultural systems can enhance crop productivity, reduce input costs and encourage more sustainable farming practices [3].

Traditional Machine learning algorithms such as decision trees, support vector machines, and gradient boosting models are used for early crop recommendation systems. These methods achieved promising predictive performance because of their simplicity, efficiency and ability to work effectively with moderate sized datasets. Among them, Random Forest method has emerged as widely adopted approach to assess soil fertility due to its robustness against noise and overfitting. However, most of the traditional models are incapable of capturing complex nonlinear relationships that exists between soil nutrients and environmental factors. As agricultural datasets is continue to grow in size and diversity, the shortcomings of these methods are becoming increasingly apparent that insist the need for more advanced learning frameworks [8].

Researchers have investigated deep learning techniques for agricultural applications to overcome these challenges [20]. Unlike traditional approaches, deep neural networks have demonstrated better representation ability in crop yield prediction, disease diagnosis, weed detection, and soil nutrient analysis [9]. A recent survey by [11] highlighted the increasing impact of deep learning in agriculture and point out its ability to learn discriminative features automatically from complex datasets. Similarly, [3] observed that the deep learning approaches generally achieve better performance than traditional machine learning methods in precision agriculture when sufficient training data are available. In another study, [24] introduced a deep learning based framework for crop and fertilizer recommendation and demonstrated its effectiveness in modeling the complex relationships among soil nutrients. Although their model was built using conventional deep learning techniques, it lacks attention based feature selection and explainability which are important for agricultural support systems.

Most deep learning methods were originally developed for sequential data and image processing. Therefore, its methods are not always well suited for the characteristics of the agricultural datasets where the information is stored typically in tabular form. This has led the researchers to explore architectures which are specifically designed for tabular learning. Among them TabNet has received considerable attention because it combines sequential attention with sparse feature selection mechanisms to identify most relevant input variables at different stages of the learning process. The model improves the prediction accuracy and interpretability by identifying the most informative features dynamically [15]. The study reported in [18] demonstrated that TabNet delivers competitive predictive performance together with transparent feature selection that making it as suitable choice for applications where model interpretability is important. However, TabNet primarily focuses on feature importance and may not sufficiently capture contextual interactions among soil attributes. This limitation highlights the need to design the model that can represent both feature importance and the contextual relationships between the soil attributes to support more reliable crop and fertilizer recommendation.

Bidirectional Long Short Term Memory (BiLSTM) networks provides and effective way to capture the contextual relationships among the input variables. Although BiLSTM was originally proposed for sequential and temporal data, recent studies have demonstrated its effectiveness in modeling structured agricultural data represented as feature sequences. [25] demonstrated that integrating BiLSTM with attention mechanisms improves crop prediction performance by learning feature interactions more effectively. [24] conducted a comprehensive review of deep learning techniques used in agriculture and reported that hybrid architectures integrating recurrent networks, attention mechanisms, and convolution models are consistently outperform standalone approaches in crop prediction, disease diagnosis, and yield estimation. They emphasized that attention based recurrent networks are preferred because they can automatically identify important features while learning nonlinear interactions among agricultural variables. Similarly, [29] proposed a CNN-BiLSTM framework integrated with an attention mechanism for crop yield and fertilizer recommendation. Their study showed that combining attention with BiLSTM improves feature representation and prediction accuracy by dynamically emphasizing influential agricultural attributes, though does not provide explicit model explainability or specialized learning for tabular soil data. A recent study by [13] proposed a hybrid framework that combines the Random Forest with an attentive BiLSTM model for agroclimatic mapping and crop yield prediction. The authors reported that the attention based recurrent architectures learn more informative feature representations than conventional machine learning approaches and standalone recurrent networks.

In the current scenario, explainability has become an important consideration in AI-based agricultural decision support systems. While deep learning models are capable of delivering high predictive accuracy, its black box nature often limits its practical use in agriculture. Stakeholders including farmers, agronomists and policy makers require a clear justification for crop and fertilizer recommendations. Explainable Artificial Intelligence (XAI) addresses this challenge by providing insights into model predictions and revealing the contribution of individual input features [1] [12]. Among the available explainable artificial intelligence approaches, SHAP and LIME are widely used techniques because they offer intuitive explanations for the decisions made by complex machine learning and deep learning models. The study in [12] demonstrated that explainable crop recommendation system improves farmers confidence by making prediction outcomes easier to interpret. In addition, the study by [6] reported that transparent recommendations enhance greater confidence and acceptance among farmers particularly in decisions related to fertilizer management and crop planning. Further, [2] argued that the explainability has become an essential component for sustainable agricultural AI because it supports transparency, accountability, and responsible decision making.

Despite the significant progress reported in the research, but there are several research challenges remain unresolved. First, most of the existing crop recommendation systems are based on attention based tabular learning or sequence based contextual learning, but little effort has been made devoted to integrate both paradigms in a unified architecture. Second, many high performing models focuses on predictive accuracy without adequately addressing interpretability requirements which is essential for practical agricultural deployment. Third, fertilizer recommendation is often considered as a standalone task without being integrated into a unified decision support system incorporating crop prediction and explainability.

To address these gaps, this study proposes Explainable Hybrid Attention Based TabNet and BiLSTM architecture that combines the complementary strengths of TabNet, BiLSTM, SHAP and LIME for intelligent crop and fertilizer recommendation. The comparative analysis presented in Table 1 highlights these research gaps and motivates the development of the proposed framework.

Table 1: Comparative Analysis of Existing Studies and the Proposed Framework

Study	**Methodology**	**Crop Recommendation**	**Fertilizer Recommendation**	**Explainability**	**Attention Mechanism**	**Hybrid Architecture**	**Major Limitation**

[11]	Deep Learning Survey for Agriculture	Yes	Yes	No	No	No	Survey paper; does not propose a predictive framework.
[18]	TabNet	Yes	No	Yes (Intrinsic)	Yes	No	Captures sparse feature importance but lacks contextual dependency learning.
[17]	Tabular Deep Learning Review	Yes	No	No	No	No	Comparative study only; no agricultural implementati on.
[19]	AI for Soil Science	Yes	Yes	No	No	No	Focuses on soil intelligence; lacks explainability and hybrid learning.
[24]	Deep Learning Techniques in Agriculture	Yes	Yes	Limited	Limited	Yes	Review study; no unified predictive framework.
[29]	CNN–BiLSTM with Attention	Yes	Yes	No	Yes	Yes	No explainability and not optimized for tabular soil learning.
[30]	Deep Learning Crop and Fertilizer Recommenda tion	Yes	Yes	No	No	No	Lacks attention mechanism and explainable AI.
[3]	AI Models in Precision Agriculture	Yes	Yes	Limited	No	No	Review-oriented study without integrated prediction architecture.
[1]	Explainable Crop Recommenda	Yes	No	Yes	No	No	Focuses mainly on explainability

	tion (SHAP + LIME)						; fertilizer recommendation not included.
[10]	XAI for Smart Agriculture	Yes	No	Yes	No	No	Evaluates explainability techniques rather than prediction models.
[12]	Agriculture 5.0 and Explainable AI	Yes	Yes	Yes	No	No	Review-oriented study; lacks predictive architecture.
[13]	RF-Attentive BiLSTM	Yes	No	No	Yes	Yes	Designed for yield prediction; lacks explainability and fertilizer recommendation.
Proposed Framework	TabNet + BiLSTM + SHAP + LIME	Yes	Yes	Yes	Yes	Yes	Integrates sparse feature attention, contextual nutrient interaction learning, explainability, and fertilizer recommendation within a unified framework.

3. Proposed Hybrid Domain-Guided Architecture (AgriDeepFusion-XAI)

We propose AgriDeepFusion-XAI, a hybrid deep learning framework designed for intelligent crop and fertilizer recommendation using structured soil laboratory data. Our primary goal is to build an accurate and interpretable decision support system that turns soil physicochemical measurements into actionable agricultural recommendations.

Figure 1: Phases of proposed AgriDeepFusion-XAI, a hybrid attention based TabNet-BiLSTM framework with Explainable AI

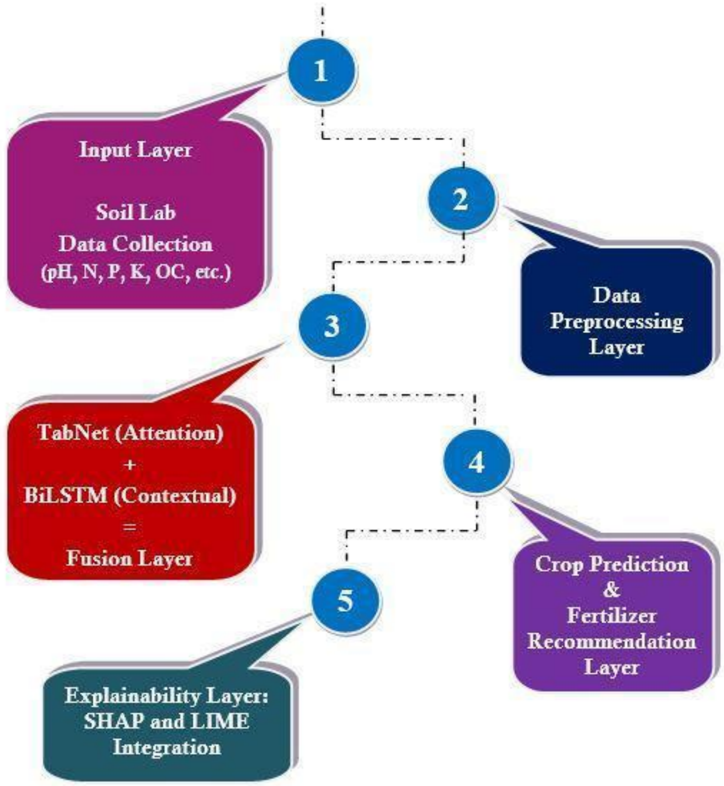

Figure 2: Internal architecture of AgriDeepFusion-XAI framework

The proposed architecture follows a pipeline in which raw soil laboratory measurements are progressively transformed into actionable agricultural recommendations depicted in Figure 1 and Figure 2. Figure 1 presents the four phase workflow of the proposed AgriDeepFusion-XAI framework. It begins with soil data acquisition and preprocessing, where laboratory measurements are converted into normalized feature representations. Next, the hybrid model development phase extracts complementary feature embeddings using attention based TabNet and sequence aware BiLSTM networks. The feature representations learned by the network are optimized through supervised learning and cross validation strategies before being interpreted with explainable AI techniques. This modular design improves reproducibility, and scalability, making it easier to integrate into real-world agricultural advisory systems. Figure 2 illustrates the overall architecture and workflow of the proposed AgriDeepFusion-XAI framework. It consists of five main components including input layer, data preprocessing layer, fusion layer, crop prediction and fertilizer recommendation layer and explainability layer. The process begins with data collection from the soil laboratory which are provided as an input to the framework. The preprocessing layer handles missing values and noisy data that ensures data consistency and reduces noise. The processed data are then passed through two parallel learning branches. The feature embeddings generated by these two branches are combined through a fusion layer to generate a unified representation of an input data. This fused representation serves as the basis for crop prediction and fertilizer recommendation. Finally, the explainability layer applies XAI techniques to provide both global and local interpretations of the model decisions which enable users to understand the factors influencing each recommendation and thereby improving the transparency and user trust in the prediction process [10].

3.1. Data Acquisition and Preprocessing

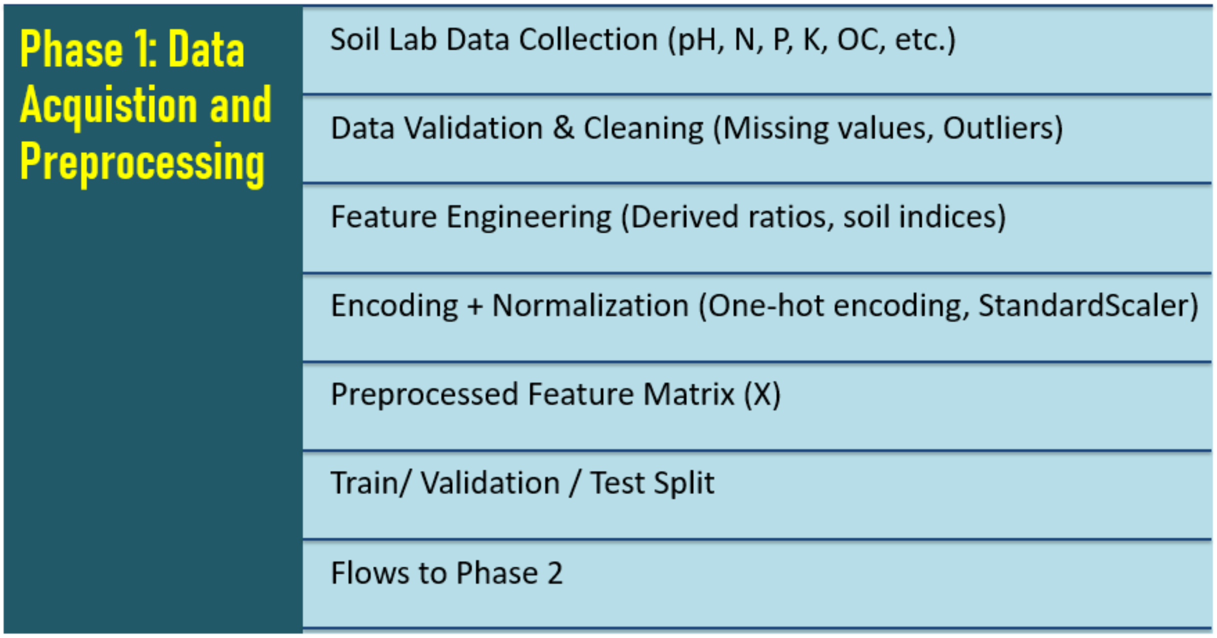

Figure 3: Phase 1: Data Acquisition and Pre-processing

The first phase (Figure 3) of the proposed AgriDeepFusion-XAI framework that primarily focuses on acquiring, organizing, and transforming raw soil laboratory measurements into a structured format suitable for deep learning analysis. For this study, we gathered data from soil lab located in Madurai, Tamil Nadu, India. The dataset includes seven years of data from 2018 to 2025, captures a diverse range of soil samples and farming conditions. The dataset includes soil characteristics, such as pH, EC, OC, and both macro and micro nutrients such as N, P, K, Zn, Fe, B, and more. Each soil sample is associated with a target crop class, enabling supervised learning across 22 different crop categories.

Table 2: Features of Soil Dataset

	Macro Nutrients	**Nitrogen (N)**
		Phosphorus (P)
		Potassium (K)
		Sulfur (S)
	Micro Nutrients	Zinc (Zn)
		Iron (Fe)
		Copper (Cu)
		Manganese (Mn)
		Boron (B)
	Physical and Chemical Properties	Soil pH
		Electrical Conductivity (EC)
		Organic Carbon (OC)

		L.S
		TEX
		Soil Colour
	Target Variable	Crop

The dataset used in this study was represented as

$$D = \{(x_i, y_i)\}_{I=1}^{N} \quad (1)$$

Where x_i is the soil feature vector of the ith sample and y_i is the corresponding crop label. This region specific dataset is based on the observations from soil lab located in Madurai, Tamilnadu, But the diversity in region and time helps the model to generalize better to different field conditions. Moreover, the proposed ensemble learning methodology is generic and data driven, which can makes it applicable to soil based datasets from other geographic regions, if the appropriate retraining and calibration are performed with the data specific to that region. The columns of the sample datasets are shown in the Table 2 for reference.

The collected data are preprocessed to improve the data quality and ensure the reliability before the model development. During this stage, missing values are imputed using statistical methods such as mean, median imputation or k-nearest neighbor imputation, outliners are identified and removed using inter quartile range (IQR) or z-score thresholds, categorical variables are encoded using one-hot or label encoding techniques if it is present and numerical features are normalized to a comparable scale. In this study, each feature x is transformed using standardization as follows:

$$x_i' = \frac{x_{i-}\ \mu_i}{\sigma_i} \quad (2)$$

Where x_i' is the standardized feature value, μ_i and σ_i are represent the mean and standard deviation of feature i, respectively. This transformation produces features with zero mean and unit variance to improve the numerical stability and efficiency of optimization of the proposed hybrid deep learning model. The dataset is divided into training, validation, and testing subsets using stratified splitting to preserve the distribution of classes across the crop categories. Stratified splitting is particularly important for agricultural datasets where the number of samples corresponding to different crops may vary significantly. Furthermore, the model training involves fivefold cross validation to obtain robust and unbiased estimates of predictive performance. In this phase, the output is a structured feature matrix $X \in Rn \times d$ and label vectors for crop class and fertilizer type, which are sent as an input to Phase 3 (Figure 4).

3.2. Hybrid Model Development

Phase 2 (Figure 4) is the core innovation of the framework, a hybrid architecture that combines TabNet and BiLSTM branches. TabNet utilizes sparse attention masks to focus on the most informative soil attributes and the BiLSTM branch captures forward and backward dependencies to learn contextual relationships among soil properties. The outputs of both branches are concatenated and projected into single latent space for final predictions. The framework adopts a dual branch design, which enables the framework to control the powers of both the attention based and the sequence based learning paradigms.

3.2.1. TabNet Branch: Sparse Feature Attention Modeling

The proposed framework incorporates the TabNet branch, a deep neural network specifically designed to learn from tabular data [18] [28]. It differs from conventional or convolutional feedforward neural networks which process all features equally. TabNet select features sequentially using attention masks that enable the model to focus on the relevant soil attributes that contribute most to the prediction task at each decision step. For given input X, the feature transformer first extracts an intermediate representation which is subsequently used to generate a sparse attention mask. A sparse attention mask is computed using the sparsemax activation function, which promotes sparse feature selection and improves the interpretability of the learning process as follows

$$M_t = sparsemax(P_t) \qquad (3)$$

where M_t is the attention mask at the decision step t, H_t represents the transformed feature representation, P_t denotes the processed prior scale features. The sparsemax activation function generates a sparse attention distribution by assigning zero weights to less informative features [9]. This mechanism allows the model to concentrate on the soil agronomic attributes that contribute most to the prediction task such as soil pH, nitrogen content, and potassium concentration. The resulting feature representation is expressed as

$$\widetilde{X_t} = M_t \cdot X \qquad (4)$$

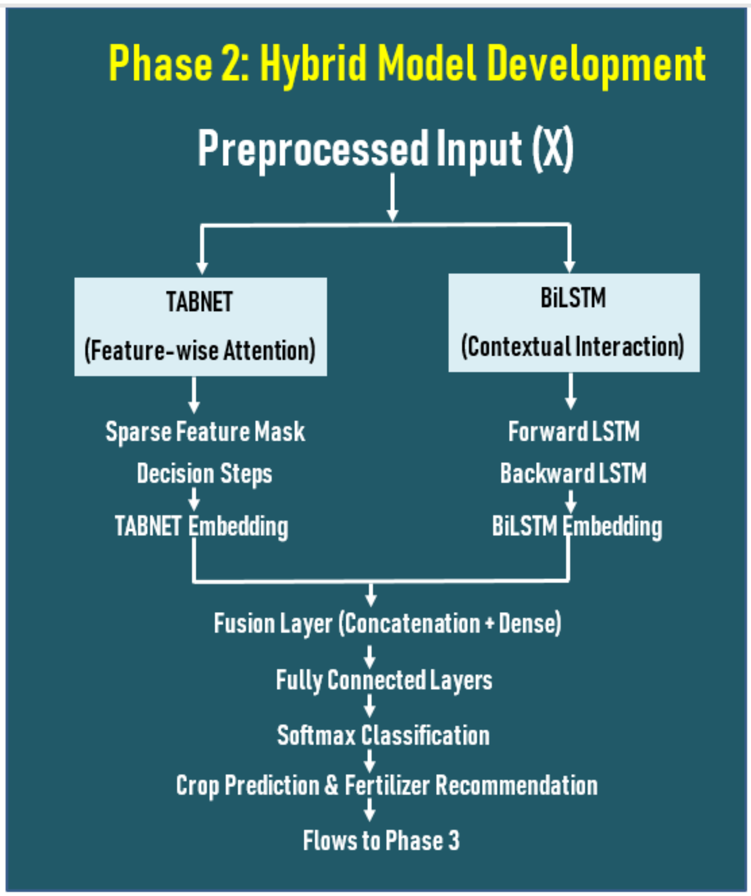

Figure 4: Phase 2: Hybrid Model Development

where dot denotes the element wise multiplication.

The masked feature representation is subsequently passed through a feature transformer which extracts higher level representations for the following each decision step:

$$H_t = f(X_t; \theta_t) \qquad (5)$$

The final feature embedding produced by TabNet branch is the output of aggregated results obtained from all decision steps:

$$E_{TabNet} = \sum_{t=1}^{T} H_t \qquad (6)$$

where T denotes the number of sequential steps. The resulting embedding captures the relative importance of input patterns and provides interpretability by integrating information learned across successive stages. For example, when the input data indicates the nitrogen deficiency, the attention mechanism automatically assigns higher weights. This adaptive weighting allows the model to make the prediction process more transparent and agronomically meaningful.

3.2.2. BiLSTM Branch: Contextual Feature Interaction Modeling

Although soil data are not time dependent, it is important to note that there is a strong nonlinearity and context dependency in the data. Many soil attributes are interacting with one another rather than acting independently. For instance, phosphorus availability is significantly influency by soil pH, while organic carbon plays an important role in nitrogen retention and microbial activity. The proposed framework incorporates a Bidirectional Long Short-Term Memory (BiLSTM) as the second branch of the architecture to capture contextual interactions among the input features [13].

The input vector is reshaped into pseudo-sequence:

$$X_{Seq} \in R^{d \, X \, 1} \tag{7}$$

Where each soil attributes is treated as an element in an ordered feature sequence. The feature sequence is organized according to an agronomic relevance and standard soil testing practices. It begins with physicochemical properties such as pH and electrical conductivity followed by macro and micro nutrients. This ordering provides a meaningful structure that enables the BiLSTM to learn contextual relationships among soil attributes in a manner that aligns with soil science principles. Once the ordered sequence is constructed, each LSTM cell employs a series of gating mechanisms to regulate the information flow. Forget gate is defined as

$$f_t = \sigma \left(W_f \, x_t + U_f \, h_{t-1} + b_f \right) \tag{8}$$

which determines how much information is retained from the previous memory state.

Input gate is represented as

$$i_t = \sigma \left(W_i \, x_t + U_i \, h_{t-1} + b_i \right) \tag{9}$$

which controls how much new information enters the memory cell.

The Candidate memory state is represented as

$$\widetilde{c_t} = tanh(W_c x_t + U_c \, h_{t-1} + b_c \,) \tag{10}$$

And the cell state is updated as

$$c_t = \; f_t \cdot c_{t-1} \; + \; i_t \cdot \widetilde{c_t} \tag{11}$$

The hidden state of the LSTM cell is then obtained by

$$h_t = \; o_t \cdot \; tanh(c_t) \tag{12}$$

where o_t denotes the output gate.

To capture bidirectional dependencies, the sequence is processed in both forward and backward directions as

$$h_t = [\overrightarrow{h_t}; h_t^{\leftarrow}] \tag{13}$$

The final contextual representation generated by the BiLSTM branch is expressed as

$$E_{BiLSTM} = \; concat(\overrightarrow{h_t}; h_t^{\leftarrow}) \tag{14}$$

This bidirectional learning mechanism enables the model to capture nutrient synergy and antagonistic relationships among soil properties by producing richer feature representations than conventional feedforward architectures.

3.2.3. Feature Fusion and Output Layer

The embeddings generated by the TabNet and BiLSTM branches are combined together to integrate the complementary strengths of sparse attention and contextual modeling. The embeddings are concatenated as

$$E_{fusion} = [E_{TabNet}; E_{BiLSTM}] \quad (15)$$

The fused vector is then passed through a dense projection layer:

$$Z = ReLU(W_f E_{fusion} + b_f) \quad (16)$$

Where W_f denote the learnable weight matrix and b_f denote the bias vector of the fusion layer. The final crop probability distribution is obtained using softmax function is

$$\hat{y}_{crop} = softmax(W_c Z + b_c) \quad (17)$$

Where $\hat{y} \in R^C$ and C represents the number of crop classes.

The predicted crop class is obtained as follows:

$$\hat{c} = argmax(\hat{y}) \quad (18)$$

The attention driven and context driven representations are combined by using the fusion mechanism to improve the prediction accuracy and minimize the loss of discriminative features during the learning process.

3.2.4. Decision Support Layer: Fertilizer Recommendation

In addition to the crop prediction, the proposed framework utilizes agronomic rule-based logic to recommend fertilizer. The amount of nutrients are categorized into three categories such as low, medium, and high based on the threshold values. For example:

$$F = \{Urea, N < T_N \; DAP, P < T_P \; MOP, K < T_K \; Balanced, Otherwise \quad (19)$$

Based on the level of nutrient deficiency identified and predicted crop selection, the fertilizer recommendation system recommends fertilizers including Urea, Diammonium Phosphate (DAP), or Muriate of Potash (MOP), or NPK based fertilizer. The combination of learned representations from deep learning model with agronomic rule based reasoning ensures that the recommendations are both data driven and scientifically consistent with the established soil nutrient management practices.

3.3. Model Training & Optimization

The performance of a hybrid deep learning framework mostly depends on the architectural design and the methodology adopted for training and optimization. The wrong training strategy may lead to overfitting, convergence issues, or low accuracy, particularly when a researcher dealing with agricultural datasets characterized by heterogeneous soil properties and varying crop distributions. That is why we tried to pay considerable attention to the choice of training methodology to make sure that our framework would learn robust feature representations and achieve reliable prediction performance from the input data. The primary objective of the training process is to minimize the difference between the predicted crop classes and the corresponding crop labels while learning the meaningful latent representations of the soil fertility. Figure 5 below illustrates how we trained and optimized our AgriDeepFusion-XAI framework. The process begins with the normalized soil dataset which is partitioned into training, validation, and testing subsets. During training, the input samples are propagate through the architecture to generate crop predictions and fertilizer recommendations. The prediction error is computed using an appropriate loss function, and the model parameters are updated iteratively through gradient based optimization. The validation stage continuously monitors the model performance to identify the optimal set of parameters and reduce the risk of overfitting. Once training is complete, the final model is evaluated using multiple performance metrics to assess its predictive capability and generalization ability. The model is trained using the following categorical cross-entropy loss function.

$$£ = -\sum_{i=1}^{C} \quad y_i \, log(\hat{y}_i) \qquad (20)$$

The optimization of the network is performed using the Adam optimizer with adaptive learning rate scheduling.

Hyperparameter tuning includes optimization of learning rate, batch size, number of TabNet decision steps, LSTM hidden units, dropout rate, and fusion layer dimensions. Hyperparameter optimization techniques, including grid search or Bayesian optimization strategies are employed to explore the parameter space efficiently and identifying near optimal configurations. The optimized hyperparameter configuration of the proposed framework is illustrated in Table 3.

Table 3: Hyperparameter configuration of the proposed framework

Parameter	Value
TabNet Decision Steps	3
Attention Function	Sparsemax
BiLSTM Layers	2
Hidden Units	128
Dropout Rate	0.3
Fusion Layer Dimension	256
Batch Size	32
Optimizer	Adam
Initial Learning Rate	0.001
Maximum Epochs	100
Early Stopping Patience	15

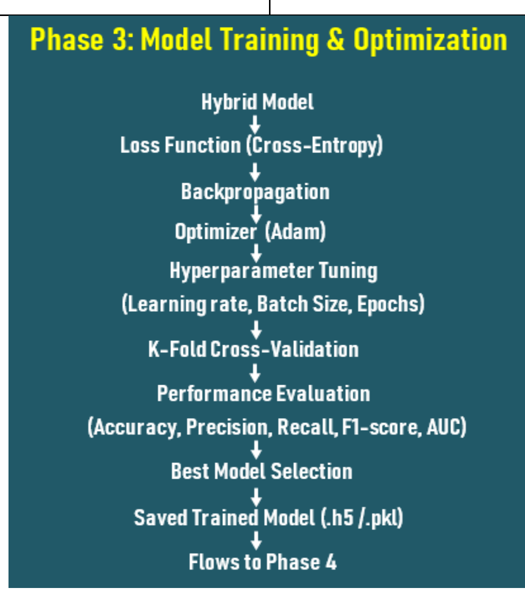

Figure 5: Phase 3: Model Training & Optimization

Model performance is evaluated using accuracy, precision, recall, F1-score, and ROC-AUC metrics. K-fold cross-validation ensures generalizability. The output of this phase is an optimized hybrid model that is capable of producing accurate and reliable crop and fertilizer recommendations. The trained model is subsequently integrated with explainable AI techniques and deployment components which are discussed in the following section.

3.4. Explainability and Deployment

Figure 6: Phase 4: Explainability & Deployment

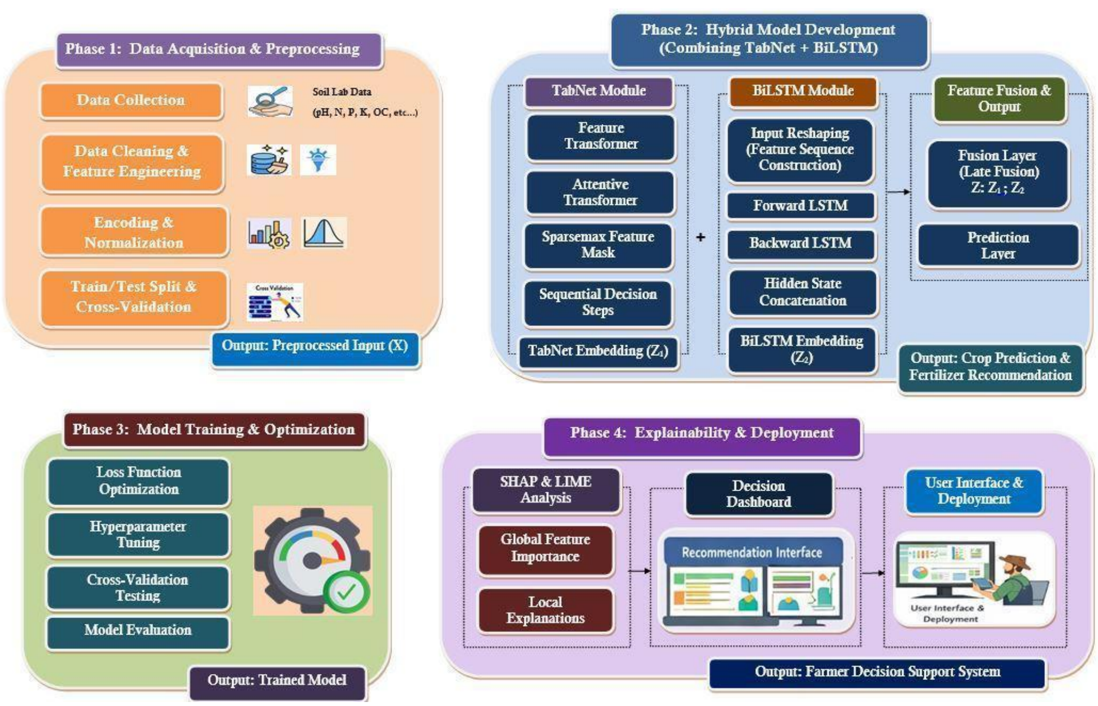

Figure 7: AgriDeepFusion-XAI, a hybrid deep learning framework

Although deep learning models deliver high predictive accuracy, their black box nature often limits their acceptance in agricultural decision making. The proposed AgriDeepFusion-XAI framework incorporates Explainable Artificial Intelligence (XAI) techniques to improve transparency and user trust. Figure 6 illustrates the explainability and deployment framework [6]. The trained hybrid model forwards the predictions to the explainability module, where SHAP and LIME identify the contribution of individual soil attributes [16].

The SHAP value of feature (i) is computed as

$$\emptyset_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|} [f(S \cup \{i\}) - f(S)] \quad (21)$$

where $\emptyset_i$ quantifies the marginal contribution of feature i. LIME generates local surrogate linear models to approximate prediction behavior around individual samples. The optimization objective of LIME is defined as follows:

$$\hat{f}(x) = w_0 + \sum_{i=1}^{d} w_i x_i \quad (22)$$

The resulting explanations generated by LIME are then displayed through an interactive interface that enables the users to understand the factors that influence the model's recommendations. For practical deployment, the trained AgriDeepFusion-XAI model is serialized and made available through a REST API or web dashboard interface. This deployment architecture supports real time inference using soil laboratory data as input. Soil laboratory inputs entered by farmers or agronomists are preprocessed and passed to the hybrid model, which produces the crop and fertilizer recommendations together with their corresponding interpretability insights as an output.

4. Experimental Setup and Evaluation

This section describes the characteristics of the dataset, the setup of our implementation environment and evaluation methods to validate our approach. The experiment was developed to facilitate a fair comparison with the machine learning and deep learning baseline models while also ensuring the reproducibility and statistical reliability of the results.

4.1. Dataset Description

The experimental dataset comprises laboratory tested soil samples collected from a soil laboratory in the Madurai region and it is characterized using key physicochemical properties. It includes essential macro nutrients (N, P, K), pH, electrical conductivity (EC), organic carbon (OC), and selected micronutrients. Contextual environmental variables such as rainfall and temperature were also included to provide additional information that is relevant to crop suitability. The soil and environmental attributes used in this study are summarized in Table 2.

The dataset was preprocessed in Phase 1 and transformed into a structured feature matrix suitable for subsequent model development. The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets to preserve class balance across crop categories. Five-fold cross validation was additionally employed to assess the stability of the model and reduce the influence of sampling variation on the evaluation results.

4.2. Implementation Details

The proposed AgriDeepFusion-XAI framework was implemented using the PyTorch deep learning framework. The proposed model combines a TabNet branch for adaptive feature selection and a BiLSTM branch for learning the contextual relationships among the soil attributes [21][24][29]. The TabNet component was configured with three sequential decision steps and sparse attention masks used at each step to identify and emphasize the soil features that contribute more for the prediction task. The BiLSTM branch contained two bidirectional recurrent layers with 128 hidden units to capture complex relationships among soil properties. A dropout rate of 0.3 was applied to reduce overfitting. The fusion layer fused embeddings from the both branches and projected them into a 256-dimensional latent space using a fully connected layer with ReLU activation. The output layer used softmax activation for multi-class crop classification. The model was trained using the Adam optimizer with an initial learning rate of 0.0001. The architecture was trained using a batch size of 32 and a maximum of 100 epochs. Early stopping was triggered if the validation loss did not improve for 15 consecutive epochs to prevent unnecessary training and to retain the model corresponding to the lowest validation loss. The optimized hyperparameter configuration of the proposed framework is illustrated in Table 3.

4.3. Evaluation Metrics

The performance of the proposed framework was assessed using widely accepted multi-class classification metrics namely accuracy, precision, recall, F1-score and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) to ensure the balanced evaluation from statistical and practical perspectives. The mathematical formulations used for evaluation are given in Equations (23) - (26).

Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{23}$$

Precision:

$$Precision = \frac{TP}{TP+FP} \tag{24}$$

Recall:

$$Recall = \frac{TP}{TP+FN} \tag{25}$$

F1-score:

$$F1 - score = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \tag{26}$$

Additionally, ROC-AUC was calculated for each class using a one versus rest strategy (OvR) approach to assess the model's ability to distinguish each class from the remaining classes. This provides a more comprehensive evaluation of the model's discriminative performance in a multi-class classification setting.

5. Results and Discussion

We compared our hybrid model with several widely used baseline models, including Support Vector Machine (SVM), Random Forest, standalone BiLSTM, and standalone TabNet. Table 3 summarizes the performance of the proposed framework alongside these baseline approaches. The results indicate that the hybrid architecture consistently achieved better performance across all evaluation metrics, demonstrating the advantage of combining attention based feature learning with contextual sequence modeling. The comparative results are illustrated in Figure 8. As shown in Figure 9, most crop categories were classified correctly, with only a few misclassifications occurred among crops with similar soil nutrient characteristics highlighting the model's ability to effectively distinguish between closely related classes.

Table 4: Comparative Performance of Proposed Hybrid Model with Traditional and Standalone Models

Model	Accuracy (%)	Precision	Recall	F1-score
SVM	88.7	88	87	87
Random Forest	91.2	91	90	90
BiLSTM	93.8	93	94	93
TabNet	94.6	95	94	94
Proposed Hybrid	97.3	97.85	97	97.92

The proposed framework was evaluated using stratified five-fold cross validation. The experimental results show that AgriDeepFusion-XAI achieved classification accuracy of 97.3%, with a macro-F1 score of 97.92%, precision of 97.85% and recall of 97.0% which improved the overall classification accuracy of standalone TabNet and BiLSTM models by approximately 3-4%. To examine further the robustness of the model, its performance was analyzed across all five fold cross validation folds. The model achieved a mean classification accuracy of 97.3%, indicating stable and reliable performance under different training and testing partitions. The improvement observed in the hybrid framework can be attributed to the complementary strengths of its constituent components. First, TabNet employed sparse attention to identify the most informative soil attributes, giving greater emphasis to key parameters such as N, P, K, and pH. Second, the BiLSTM component learned complex contextual relationships among soil properties, enabling the model to capture nonlinear interactions that influence crop suitability. Finally, the fusion layer combined the feature representations generated by both branches, allowing the model to exploit representations generated by both branches, allowing the model to exploit complementary information while minimizing the loss of relevant features. The findings of the ablation study further support the effectiveness of the proposed architecture. Removing either the TabNet or BiLSTM branch resulted in a reduction of approximately 2-3% in classification accuracy, indicating that both components make meaningful and complementary contributions to the overall predictive performance of the framework.

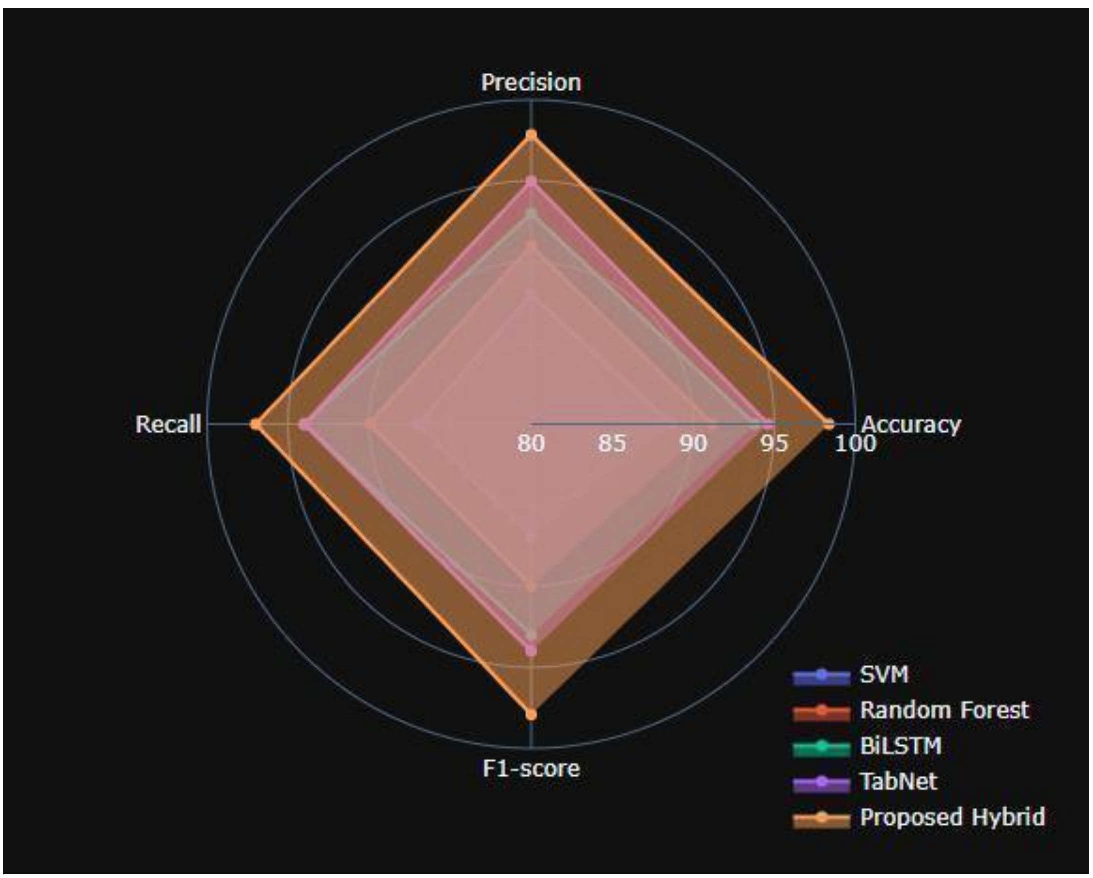

Figure 8: Comparative analysis of proposed framework with traditional algorithms

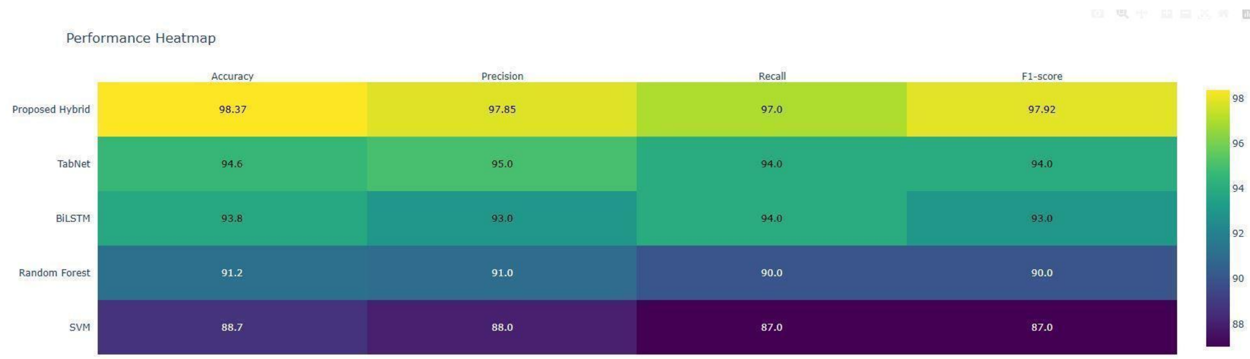

Figure 9: Confusion Matrix

6. Conclusion and Future Work

AgriDeepFusion-XAI, A hybrid explainable deep learning framework is presented in this study that combines TabNet for feature selection based on attentive learning and BiLSTM for capturing contextual relationships among soil attributes for crop and fertilizer recommendation. The combination of the sparse attention mechanism in TabNet and the contextual learning capability of BiLSTM achieved more effective feature representation and better predictive performance. Furthermore, the explanations generated by SHAP and LIME enhanced the transparency of the model by identifying the key soil features that contributed to prediction process which increase its practical value for precision agriculture applications. The experimental results demonstrate the effectiveness of the proposed architecture. The proposed framework attained a classification accuracy of 97.3% and maintained consistent performance during cross validation, indicating the robustness of the proposed approach. However the proposed framework achieved promising results, the study has some limitations. The proposed framework was evaluated using soil data which is obtained from a particular geographical area and its performance should be further tested with the data from various regions and cropping conditions in order to evaluate its generalizability. Furthermore, the current model is mainly focuses on soil laboratory measurements and it does not include other factors such as weather conditions, irrigation practices, remote sensing data or real time field observations which may also affect crop and fertilizer recommendation. Future research will focus on incorporating multimodal agricultural data sources such as satellite imaginary, measurements from IoT based soil sensor and real time meteorological data in order to increase the adaptability to different field conditions. Further exploration of transformer based architectures and federated model may also improve the representation learning and enable collaborative model development without compromising data privacy. Finally, large scale validation carried out with farmers and agricultural experts would helpful to assess the usability and practical effectiveness of the proposed system under real world farming conditions. In general, the findings indicate that the proposed explainable hybrid framework that combines attention based feature selection with contextual learning can produce accurate and interpretable crop and fertilizer recommendations. The results shows that the proposed method offers a promising direction for developing data driven, transparent and decision making support system for precision agriculture.

Conflicts of Interest

The authors declare that they have no conflict of interests.

Funding Statement

Not applicable.

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