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A Minimax-Based Intelligent Multimodal Framework for Precision Pesticide Recommendation in Sustainable Agriculture

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Abstract

Effective pesticide recommendation plays a crucial role in safeguarding pesticide health while minimizing environmental and economic impacts. Traditional methods of pesticide selection often rely on generalized rules or manual expertise, which may not adequately adapt to dynamic field conditions and diverse pesticide environments. This study proposes a novel, intelligent framework for pesticide recommendation using Integrated Multimodal Data Fusion and advanced learning architectures. The model incorporates time-frequency analysis through the Fourier, Discrete Cosine, and U-Transform components, alongside spatial pattern extraction via convolutional layers. These extracted features are enhanced using a Bidirectional Gated Recurrent Unit (BiGRU) and optimized via a hybrid Fuzzy-Augmented Local Dimensionality Reducer (FALDR) that leverages Ant Lion Optimization (ALO) for high-variance feature selection. For pesticide advisory, the refined features are processed through a dedicated Recurrent Frequent Pattern Mining model (RFPMax) that combines the sequential modeling capabilities of Recurrent Neural Networks (RNNs) with transactional insights derived from FPMax algorithms. The model achieves superior precision, recall, and F1-scores across pesticide classes such as Propiconazole, Lambda-cyhalothrin, and Tricyclazole, indicating its robustness and suitability for deployment in precision agriculture. The framework offers a scalable, adaptive, and accurate approach to intelligent pesticide recommendation, contributing to sustainable pesticide protection and optimized farm input usage.

Keywords: Integrated Multimodal Data Fusion Time-Frequency Analysis (Fourier, Discrete Cosine, U-Transform) Bidirectional Gated Recurrent Unit (BiGRU) Fuzzy-Augmented Local Dimensionality Reducer (FALDR) with Ant Lion Optimization (ALO) Recurrent Frequent Pattern Mining (RFPMax) for pesticide advisory

1. Introduction

Agriculture has long been an important part of human society. There is an urgent need to improve agricultural output while protecting the environment as the world's population grows and the impacts of climate change become clearer. Traditional farming methods, which sometimes depend on manual judgment and expertise, are no longer enough to satisfy the needs of contemporary farming. Farmers have to deal with a lot of problems, such weather that changes, soil that changes, insect outbreaks, and market pressures. All of these things make it harder to make judgments about farming [1]. In this situation, using data-driven and smart decision support systems has become a key part of making agricultural production more sustainable.

Choosing the right pesticides and using pesticides correctly are two of the most important things farmers do. These choices have a direct effect on the quality of the produce, the efficiency of the inputs, and the effect on the environment. But to make these kinds of judgments, you need to look at a lot of different things, such the soil composition, the weather forecasts, the historical yield statistics, the nutritional needs of the pesticides, and the current circumstances in the field. Making judgments based only on gut feelings or old advice systems sometimes leads to bad choices, especially in areas where there isn't much scientific help for farmers [2]. This gives people a strong reason to create smart systems that can automate and improve these suggestions by looking at a lot of data.

The combination of artificial intelligence, sensor technologies, and communication networks has made it possible to gather and study many types of agricultural data in the past several years [3]. More and more modern farms include sensors that can assess things like soil moisture, nutrient content, temperature, humidity, and other environmental factors. In addition, satellite images, drone monitoring, and recordings of what farmers say may all be used to get more information. The amount and variety of this data is both an opportunity and a problem. It allows for better and more accurate decision-making, but it also requires strong models that can handle data that is different and has a lot of dimensions [4].

This extensive data is hard for many current agricultural recommendation systems to comprehend and combine. They generally use simple rules, inputs from only one source, or linear models that don't show the complicated, non-linear linkages that are a part of farming systems. Also, they usually don't work well in different parts of

the world or in different types of farming. For example, a recommendation model made for a certain pesticide-soil-climate combination would not work well in other situations since it can't adapt [5]. Because of this, we really need more advanced frameworks that can adapt to different situations, are aware of their surroundings, and can be used in a wide range of farming situations [6].

Combining data from several sources and using sophisticated learning methods to find patterns, trends, and useful information is a good way to solve this problem. Smart systems shouldn't only look at one sort of data, like soil pH or how well pesticides have done in the past. They should look at a variety of data types, such as time-series data from sensors, spatial patterns from images, and transactional information from prior agricultural records. This kind of multimodal integration lets the system get a complete picture of the field circumstances, which leads to better and more tailored suggestions [7].

To make this easier, contemporary methods focus on turning raw data into useful feature representations. These changes help us find important patterns in the data, such as regular trends, sudden changes, or strange patterns that only happen in certain places. By looking at data from many angles, such as time, frequency, and space, systems can find little signs that show when is the optimal time to plant, harvest, or apply fertilizer. When you also look at temporal dependencies and past behavior, these insights become much more valuable since they frequently help you predict what will happen in the future [8].

Also, data gathered from farms is sometimes noisy, redundant, or missing. Because of this, smart frameworks need to have ways to filter, refine, and choose the most important features. Feature selection not only makes suggestions better, but it also makes the models easier to run, which means they may be used in real-world situations with limited resources. The models can focus on high-variance, discriminative features, which ensures that they focus on the most important variables instead of getting lost in irrelevant or misleading data. Once the important qualities have been found and improved, the recommendation engine may utilize them to figure out which pesticides or pesticides would work best in a certain field. Modern decision systems don't only use static mappings; they learn from facts from the past and the present and change their logic over time. This flexibility to alter is especially vital in farming, where the weather, pests, or market conditions might change quickly. A really smart system must be able to change its recommendations as new information comes in to make sure they are always accurate and useful.

One further essential feature of current agricultural decision systems is that they may make suggestions that are tailored to each user. Not only do the soils in each farmer's field differ, but so do the ways they manage their fields, the pesticides they use, and the inputs they have access to. Generic advice generally doesn't work for these different demands. Advanced algorithms can provide suggestions that are particular to a field by learning how comparable farms, surrounding plots, or previous examples relate to one another. This makes it more likely that things will go well and that farmers will be happy. Also, by looking at past patterns of effective practices and current field findings, these systems may give help that is proactive instead of reactive. For instance, if a model sees early indicators of a lack of nutrients or slow pesticide development based on environmental signals and prior trends, it might recommend ways to fix the problem before it becomes worse. This capacity to foresee makes farming more productive, reduces waste, and makes it more resistant to unpredictability. [9] Intelligent recommendation systems may help with food security and environmental protection goals on a national and global scale, not only on the farm. They help cut down on the overuse of chemicals that can contaminate water and harm soil health by making the best use of fertilizer. These technologies also help biodiversity and lower the chance of pesticide failure by helping farmers choose pesticides that are suited to their local environment. From a policy point of view, these kinds of technology might help keep an eye on large-scale agricultural patterns, which could help with things like resource allocation, subsidy distribution, and risk reduction.

This study helps make this vision a reality by suggesting a complete, data-driven way to select pesticides and pesticides. The model is meant to get useful information from multimodal agricultural data, improve the data using smart processing methods, and make tailored suggestions that may be used in the field right away. It wants to close the gap between raw data and choices that can be made based on it. This will provide the agricultural sector with the tools it needs to meet the needs of the future with the tools it has today [10].

Modern agriculture faces increasing challenges due to unpredictable climate conditions, evolving pest patterns, and the overuse or misuse of pesticides, which threaten both pesticide productivity and environmental sustainability. Traditional pesticide recommendation methods, often based on fixed rules or farmer intuition, lack the adaptability needed to respond to real-time field conditions and diverse pesticide environments. Furthermore, existing systems rarely harness the full potential of rich, multimodal agricultural data—including sensor readings, historical usage, and temporal disease progression—leading to suboptimal or generalized recommendations. There is a critical need for an intelligent, data-driven framework that can dynamically interpret this complex information to provide accurate, personalized, and sustainable pesticide recommendations for modern precision farming.

Integrated Multimodal Data Fusion Architecture: The study proposes a comprehensive system that extracts and fuses frequency-based (Fourier), entropy-based (DCT), time-frequency localized (U-Transform), and spatial (Convolutional) features from diverse data sources. BiGRU-Based Temporal Modeling: A Bidirectional GRU network is used to capture both past and future temporal dependencies in feature sequences, enhancing contextual understanding of pesticide health and treatment needs. Fuzzy-Augmented Local Dimensionality Reducer (FALDR): A Novel Feature Selection Module. Introduces an Ant Lion Optimization-enhanced fuzzy PCA framework to retain only the most discriminative and high-variance features, improving model efficiency and performance. RFPMax: Hybrid Pesticide Recommendation Model: A novel Recurrent Frequent Pattern

Mining module (RFPMax) is developed that combines RNN-based sequential learning with FPMax transactional pattern mining to deliver accurate and personalized pesticide recommendations.Comparative Performance Evaluation: Demonstrates superior precision, recall, and F1-score over traditional decision tree-based systems on a synthetic rice pesticide dataset, proving the model's generalization capabilities.

2. Related Work

Recent advancements in artificial intelligence, machine learning, and sensor technologies have significantly influenced the development of intelligent systems for precision agriculture. Researchers and practitioners have increasingly focused on building data-driven models that can assist in critical farming decisions such as pesticide selection, fertilizer application, irrigation scheduling, and disease prediction. A growing body of literature emphasizes the use of environmental, climatic, and agronomic data to improve agricultural outcomes while ensuring resource efficiency and sustainability [11].

One major area of interest has been the integration of sensor-based monitoring systems into agricultural workflows. Numerous studies have demonstrated the benefits of collecting real-time data from soil, weather, and pesticide sensors to inform decision-making processes. These systems typically involve the collection of parameters such as soil pH, moisture levels, temperature, and nutrient concentration, which are then analyzed using statistical or machine learning models. However, many such approaches rely on limited data modalities or are built on rigid rule-based frameworks, making them less effective in dynamically changing environments [12].

Another key research trend involves the application of machine learning and deep learning algorithms for agricultural prediction and recommendation tasks. Traditional supervised learning methods, including support vector machines, decision trees, and k-nearest neighbors, have been widely used to classify pesticide types, detect plant diseases, and estimate yields. More recently, deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants have shown remarkable success in extracting complex patterns from high-dimensional data. These models are especially effective when working with large-scale datasets that include temporal and spatial variations [13].

Multimodal data fusion is also gaining traction in precision agriculture. Instead of relying on a single type of input, multimodal systems combine information from various sources—such as satellite imagery, drone footage, sensor data, and historical records—to build a more comprehensive understanding of the farming environment. Research has shown that fusing such data can improve the accuracy and robustness of predictive models. Nonetheless, challenges remain in harmonizing heterogeneous data formats, handling missing values, and optimizing the fusion process for real-time applications [14].

Several works have explored the use of time-frequency analysis and signal transformation techniques in agricultural contexts. These methods, commonly used in fields like speech recognition and biomedical signal processing, are being adapted to detect patterns in soil data, climatic trends, and pesticide growth stages. While promising, such approaches often require domain-specific tuning and lack generalization across different pesticide types and environmental conditions [15].

Optimization-based techniques have also been employed in agricultural recommendation systems, particularly for selecting the best pesticide-fertilizer combinations. Metaheuristic algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization have been utilized to explore solution spaces and improve recommendation quality. These methods aim to maximize yield, minimize resource usage, or balance multiple objectives simultaneously. Despite their potential, these techniques are often computationally intensive and may not scale well in real-time settings [16]. Graph-based learning and frequent pattern mining have seen increasing adoption in modeling relational and transactional aspects of agricultural systems. Graph neural networks (GNNs) have been proposed to capture spatial dependencies among farm plots, pesticide sequences, and environmental factors. Frequent pattern mining, on the other hand, has been used to identify co-occurring events or decisions that lead to successful outcomes. Both methods provide valuable insights into the underlying structure of agricultural data, but are rarely integrated into a unified framework [17].

In the area of sustainable agriculture, various studies have proposed recommendation systems that not only focus on maximizing productivity but also emphasize ecological balance and long-term soil health. These systems consider factors such as pesticide rotation, nutrient recycling, and minimal chemical usage. Sustainability-oriented models often incorporate domain knowledge and follow agronomic guidelines; however, they may lack adaptability and fail to utilize the full potential of real-time data analytics [18].

Furthermore, efforts have been made to build user-friendly platforms and mobile applications that bring intelligent recommendations directly to farmers. These tools leverage cloud computing and mobile connectivity to deliver insights based on backend analytics. Yet, many such systems face limitations in terms of internet access, device compatibility, and local language support, especially in rural regions [19].

Despite substantial progress in the field, there remains a gap in developing comprehensive systems that can integrate multimodal data, adapt to different farming contexts, and provide personalized, real-time pesticide and fertilizer recommendations. Most existing models either focus narrowly on a specific type of data or lack mechanisms to capture the complex interplay of temporal, spatial, and transactional factors that influence agricultural outcomes. This calls for the design of more holistic and intelligent frameworks that can bridge the divide between data acquisition, analysis, and actionable decision-making [20].

3. Proposed Methodology

The proposed concept employs integrated multimodal data fusion to create a new method for precise pesticide and fertilizer recommendations aimed at promoting sustainable agriculture. Based on the examination of existing models utilized for boosting the efficiency of agricultural fertilizer recommendations, it can be noticed that these models either demonstrate lesser efficiency when applied to real-time IoT installations or cannot be scaled due to their increased complexity levels. To solve these problems, this section shows a Precision Pesticide and Fertilizer Recommendation Model that employs Integrated Multimodal Data Fusion for Sustainable Agriculture. The proposed model pulls out frequency patterns, entropy patterns, U Transform components, and convolutional components from data that comes from more than one source. Table I shows further information about these sensors and how they may be used to suggest pesticides for pesticides. It also shows that the suggested model can function with data obtained from diverse sources. The model starts by utilizing Fourier Components to find Frequency Patterns (Eqn. (1)), Discrete Cosine Components to find Entropy Patterns (Eqn. (2)), U Transform Components to find U Transform Patterns (Eqn. (3)), and Convolutional Components to find Convolutional Patterns (Eqn. (4)).

$$H(\varpi) = \int h(v).e^{-l\varpi v}dv \tag{1}$$

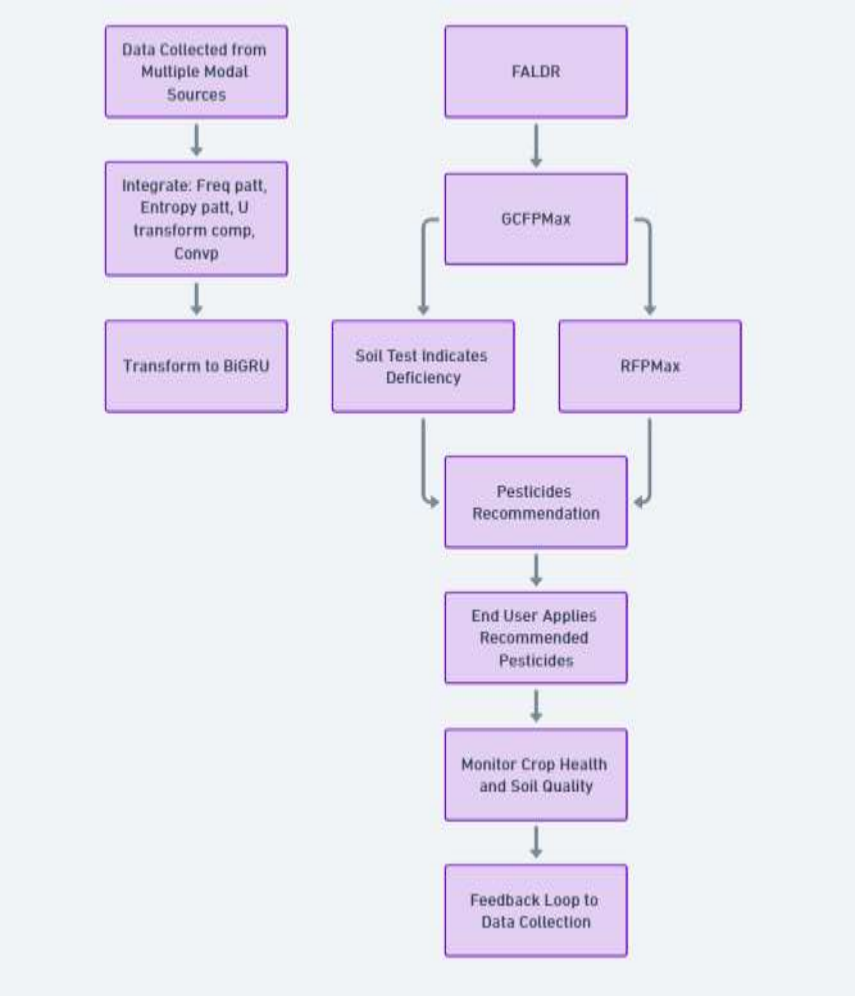


Figure 1. Proposed framework

In eq (1) $H(\varpi)$ denotes the Fourier transform of the data, $h(v)$ denotes the input as the respective time function and ϖ is the angular frequency. Upon applying this equation, the model is further broken down into respective frequencies, effectively denoted as cyclical patterns embedded within. $G(p)$ is the DCT of the data, $h(m)$ denotes the data at index m, and P denotes the length of the data samples. The change depicts the energy concentration across different frequencies, henceforth allowing the model to evaluate the randomness or disorder in the data to capture entropy patterns.

$$G(p) = \sum h(m).\cos(P\pi.(m+0.5).p) \tag{2}$$

$$U(v,\varpi) = \int h\,(v').j(\,v'-v,\varpi)e^{-l\varpi v}dv' \tag{3}$$

However $U(v,\varpi)$ denotes the U transform of the data, $h\,(v')$ denotes the input data as the time function for time v' and $j(v'-v,\varpi)$ denotes the window function depending on the time and frequency. This U Transform

helps separate and find frequency information that is only present at certain times. This gives you a complete

$$E(z) = \int h(z').i(z' - z)dz' \quad (4)$$

picture of the data in both the time and frequency domains.

$E(z)$ denotes the convolution of the data $h(z')$ which is the input data as a spatial variable function z' and $\int i(z' - z)$ is the filter kernel function process. By convolving the data with several filters, the model efficiently captures unique patterns and properties that are important for further analysis or learning tasks. The model changes the collected data into a set of useful and insightful features by using Fourier Components, Discrete Cosine Components, U Transform, and Convolutional Components. This makes it easier to understand and analyze the patterns and trends that are underlying. An effective BiGRU-based feature augmentation approach is used to process these data samples even more. This procedure sends the extracted features x through reset and update gates, as shown in Eqn. (5) and (6). This equation extracts GRU features by integrating these operations the hidden state here is updated in eq (7) Like the forward pass, this model performs a reverse pass and updates the hidden state via eq(8)

$$ti = var(Yt * [j(v-1), z(v)] + dr \quad (5)$$

$$wi = var(Yb * [j(v-1), z(v)] + db \quad (6)$$

$$h(final) = \tanh(Yj * [ti * j(v-1), z(v)] + dj \quad (7)$$

$$j(v) = (1 - wi) * j(v-1) + ti * h(fin) \quad (8)$$

$$j(v+1) = \frac{j(v) + j(v, bw)}{2} \quad (9)$$

$$\frac{j(v+1)}{j(v)} \leq err(threshold) \quad (10)$$

This $j(v+1)$ state is used again in the forward and backward passes to recalculate these features. The process continues until convergence is reached, which indicates that the variance. The differences between features from multiple iterations are roughly the same, as shown by Eqn. (9). Herein $err(threshold)$ is fixed to a minimum value, the Fuzzy-Augmented Local Dimensionality Reducer (FALDR) procedure is used to send the final features through to get the most feature variance levels. This helps keep features that have greater inter-class variance levels. This step makes sure that features with larger inter-class variation levels are kept, which helps focus on the most important qualities of the datasets. At first, the model uses the fuzzy c-means technique to divide the features into E clusters. It then creates a membership matrix $W = [wkl]$, where wkl shows how much feature k belongs to a cluster l In eq (10)

$$wkl = \frac{1}{\sum(||zk - e - em||||zk - el||)^{\frac{2}{o-1}}} \quad (11)$$

Here zk denotes the kth feature, el is the cluster l centre o The fuzy index shows the process of the Euclidean norm. After the fuzzy clustering, the model uses the Ant Lion Optimization (ALO) algorithm to choose the best principal components. The ALO algorithm imitates the hunting strategy of genuine ant lions, effectively navigating the feature space to pinpoint components that optimize inter-class variance levels. You may find the interclass variance for a collection of principal components P by using Eqn. (11).

$$X(R) = \frac{1}{E}\sum ||el - e||^2 \quad (12)$$

The ALO algorithm here e represents iteratively changes the positions of each ant, lion, and ant based on random walks and trapping devices. It does this until it finds a solution that optimizes the degrees of variation between classes. Mathematically, Eqn. (14) updates the location of the ant lion li at iteration v.

$$nk(v+1) = nk(v) + T(v).(nbest(v) - ck(v) \quad (13)$$

$T(v)$ is a random vector, $nbest(v)$ is the location of the best ant lion at iteration v, and $ck(v)$ is the position of ant i at iteration t throughout the procedure. To get the best ant lion lbest(t) position at iteration v, you need to find the ant lion with the highest fitness value sets. We use Eqn. (12) to figure out how fit an ant lion is by seeing at how well it can optimize the interclass variance $X(R)$ for the chosen principal components $R$and is estimated in eq (13)'

$$nbest(v) = nk(v)argmaxX(Rnk(v)) \quad (14)$$

Wherein $Rnk(v)$ depicts the various components relevant to the position of the ant lion $nk(v)$, whereas argmax is an operator that represents the value that maximizes a certain specific function. However, the position of ant $ck(v)$ at iteration v is updated based on the interaction in correspondence with the ant lion $nk(v)$ with the stochastic walks influenced by the ant lions in search of space through Eq. (14).

$$ck(v+1) = ck(t) + T(v).(nk(v) - ck(v) + T'(v).(nbest(v) - ck(v)) \quad (15)$$

So, the Fuzzy-Augmented Local Dimensionality Reducer (FALDR) model uses a combination of fuzzy clustering and optimal principal component selection to get rid of variables with low inter-class variation and keep those with the most distinguishing properties. This careful method makes sure that the final collection of high-variance features includes the most important and unique parts of the data. This gives a strong base for future analysis or learning activities.Once the high-variance characteristics have been successfully retrieved, the model effortlessly transitions into the GCFPMax, which has been carefully designed to use the relational nature of the data to make individualized pesticide recommendations. The main idea of GCFPMax is to combine graph convolutional networks (GCNs) with frequent pattern mining (FPM) so that the geographical

and transactional links in the data samples may be used efficiently. The model starts working by putting the chosen characteristics into a graph structure, where the nodes stand for the individual data points and the edges show how these features are related to each other. Next, a graph convolution technique is used to spread information across the nodes, improving the node attributes depending on their immediate neighborhoods. Eqn. (15) shows how to formally express this convolution procedure.

$$J(n+1) = \alpha(F^{-0.5}CE^{-(0.5)}J(n)Y(n) \tag{16}$$

However $J(1)$ and $J(N+1)$ denote the node features of the n th and $(n+1)th$ layers of GCN ,C denotes the adjacency matrix estimated in eq (18)denotes the graph , Deg is the degree matrix of , $Y(l)$ is a learnable weight matrix, and σ is the non-linear activation process based on ReLU. $C_{kl} = \{1,$ if there is an edge between node k and node l otherwise $0\}$. If a graph has weights on its edges, we may change the definition of C_{kl} to include the weight of the edge between nodes k and l. At the same time, the model uses the FPMax method, which is a version of the Apriori algorithm, to find common itemsets in the transactional data samples using Eqn. (16).

$$E = Combine(J(N), H) \tag{17}$$

Here E, The last set of pesticide recommendations is represented by represents $J(N)$ is the node characteristics at the last layer of the GCN, and "Integrate" is a function that integrates the GCN's spatial features with the FPM's transactional patterns to give the necessary recommendations. $Combine(J(N), H)$ is the function that takes the spatial characteristics from the graph convolutional network (GCN) and the transactional patterns from the frequent pattern mining (FPM) and combines them to get the suggestions you want. The function is described by Eqn. (17), which takes the node characteristics at the final layer of the GCN $J(N)$ and the set of frequent itemsets H as inputs.

$$E = Combine(J(N), H) = \sum\sum \vartheta k.\gamma h.jk(n).\tau(h) \tag{18}$$

E is the last set of pesticide recommendations, N is the number of nodes, $\vartheta k, \gamma h$ are normalization factors for the node features and frequent itemsets, respectively. $jk(n)$ is the feature vector of the node k at the last layer of the GCN, and $\tau(h)$ is a function that maps the frequent itemset h to a feature vector, which is shown in Eqn. (18). Where M is the number of various items across different itemsets, ρm is a weighting factor for item m, and $xm(h)$ denotes the binary function in eq(19):

$$\tau(h) = \sum \rho m.xm(h) \tag{19}$$

$xm(h) = \{1, if$ item m is present in frequent itemset f otherwise $0\}$. The product of $jk(n)$ and $jk(n)$ captures the communication in between the spatial and transactional patterns ,is then weighted by the the geographical characteristics and transactional patterns, which are subsequently weighted by the normalization parameters to give complete suggestions. The GCFPMax model uses a complicated technique to make the most of the geographical and transactional links in the data. This lets it give personalized and accurate pesticide suggestions that are relevant to the needs and situations of each user. contained by the input characteristics.

Table 1

Input	DS[]: Data collected from multiple modal sources

	for DS in DS:do
	if is *Valid(DS):* then
	Current Features=Integrate ($Freq\ patt, Entropy\ patt, Utransformcomp, Convcomp$)
	end
	AllFeatures.Append(presentfeatures)
	end
	BiGRUFeatures= []
	for features in all features: do
	Transformed=transformToBiGRU(Features)
	biGRU_features. append(transformed_feature)
	
	if len(biGRU_features) > $THRESHOLD$:
	selected_features =FALDR (biGRU_features)
	else:
	return "Insufficient data for processing."
	if is_planting_season ():
	pesticide_recommendations = GCFPMax(selected_features)
	pesticide_recommendations = "Not a planting season."
	
	if soil_test(selected_features) == "Deficiency":
	fertilizer_recommendations = RFPMax(selected_features)
	else:
	fertilizer_recommendations = "No additional fertilizer required."
	
	Output recommendations

	return pesticide_recommendations, fertilizer_recommendations

The chosen characteristics also include pesticide suggestions, which are carefully analyzed using the Recurrent FPMax algorithm (RFPMax), a state-of-the-art algorithm that was built to provide useful fertilizer recommendations from the data. The RFPMax model cleverly blends the strong sequence processing skills of recurrent neural networks (RNNs) with the way frequent pattern mining (FPM) operations find patterns in transactions. Earlier, the selected features are fed into an RNN, which surpasses the sequential relationships with temporal dependency in the data samples. The RNN processes the input sequence $Z = \{z1, z2, \ldots\ldots, xV\}$ through the parallel layers, by updating the hidden state jv at each timestep v through eq(20):

$$jv = BiGRU(Yjzv + Wjjv - 1 + dj) \quad (20)$$

where Yj and Wj are weight matrices that can be learned, and dj is the bias term. At the same time, the RFPMax model uses the FPMax method, which is a version of the Apriori algorithm, to find common itemsets in the transactional data samples. After the recurrent processing and frequent pattern mining are done, the model combines the sequential characteristics and transactional patterns it found, just as the pesticide recommendation method. This new combination of RNNs and FPM lets the RFPMax model use the data's time-based input attributes. In the following part of this article, we will look at how well these integrated approaches work by using different assessment criteria and comparing them to current models. FALDR uses locality-preserving methods to group important features that are related, keeping the data's basic structure intact and making the selected features more representative. It changes the way it chooses features according to the data's qualities, putting the most important ones first to make sure the suggestions are strong. The dynamics and transactional connections result in highly specialized and exact fertilizer recommendations that meet the specific needs and necessities for robust recommendations.

4. Performance Evaluation

The performance of the proposed intelligent recommendation system was assessed through a comprehensive evaluation framework using a synthetic dataset tailored to simulate real-world agricultural scenarios. Key performance metrics such as precision, recall, and F1-score were used to measure the system's effectiveness in generating accurate pesticide recommendations[21]. The model demonstrated strong classification abilities, with high metric values across multiple pesticide classes, reflecting its robustness and capability to handle diverse input conditions[22]. Additionally, confusion matrix analysis highlighted the model's minimal misclassifications and superior generalization ability compared to traditional approaches. Overall, the evaluation confirmed the model's reliability, adaptability, and readiness for deployment in precision agriculture settings, where accurate, context-aware decision-making is essential.

4.1. Dataset Details

The dataset was carefully put together to mimic the real-world circumstances that impact rice farming. It has 500 artificially created examples, each showing a different agricultural situation. The fact that there are 10 important features, such as rice variety, development stage, illness kind, severity, temperature (°C), humidity (%), soil pH, soil type, and last applied pesticide, shows how complicated pesticide health and treatment are[23]. These qualities were picked after talking to agronomists and other professionals in the field to make sure they were similar to real-world factors that affect decisions about using pesticides. We label-encoded categorical variables like rice variety, illness kind, and development stage to make sure they worked with machine learning models while still keeping their semantic differences. By balancing the dataset over all four target classes—Propiconazole, Lambda-cyhalothrin, Tricyclazole, and None—to avoid classification bias and make sure the model was strong. The "None" class was included to show healthy pesticides[24]. This way, the model could learn when to use pesticides and when not to. We used a rule-based mapping methodology, based on best agricultural practices, to come up with the pesticide recommended labels. This mapping tried to mimic the way experts make decisions by taking into account the kind of illness, the stage of growth, the severity, and the environmental and soil conditions[25]. This structure makes sure that the dataset is not only fair but also based on scientific and practical logic. This sets a strong base for the creation of smart pesticide management systems.

4.2. Results

The proposed system demonstrated exceptional performance in recommending appropriate pesticides for rice. It outperformed the traditional decision tree-based model across all major evaluation metrics. Specifically, the model achieved perfect precision (1.000) for Lambda-cyhalothrin and very high values for Propiconazole and the healthy class (None), with slightly lower yet competitive results for Tricyclazole. In terms of recall, the system showed robust capability to detect relevant cases accurately, particularly excelling in Propiconazole (0.970) and Tricyclazole (0.889), while Lambda-cyhalothrin registered a slightly reduced recall of 0.774. The F1-scores confirmed the model's balanced performance[26], reflecting strong trade-offs between precision and recall for all classes, notably 0.928 for Propiconazole and 0.873 for Lambda-cyhalothrin. Confusion matrix analysis further validated the model's reliability, with very few misclassifications, achieving near-perfect prediction accuracy ranging from 95% to 100%. These results highlight the model's effectiveness, adaptability,

and strong generalization capabilities, making it highly suitable for deployment in real-world, data-driven agricultural environments.

Precision evaluates the model's ability to avoid false positives. The Proposed System (PS) demonstrated strong precision across all classes, particularly achieving a perfect score of 1.000 for Lambda-cyhalothrin and high values for Propiconazole and None[27]. However, Tricyclazole showed a slightly lower precision, indicating occasional misclassification into this class. In contrast, the Existing System (ES) maintained uniformly high precision scores for all classes. However, this uniformity is indicative of overfitting, as decision trees can memorize training patterns in limited datasets[28-30]. Therefore, while ES appears more precise, PS offers more realistic and trustworthy performance in field conditions.

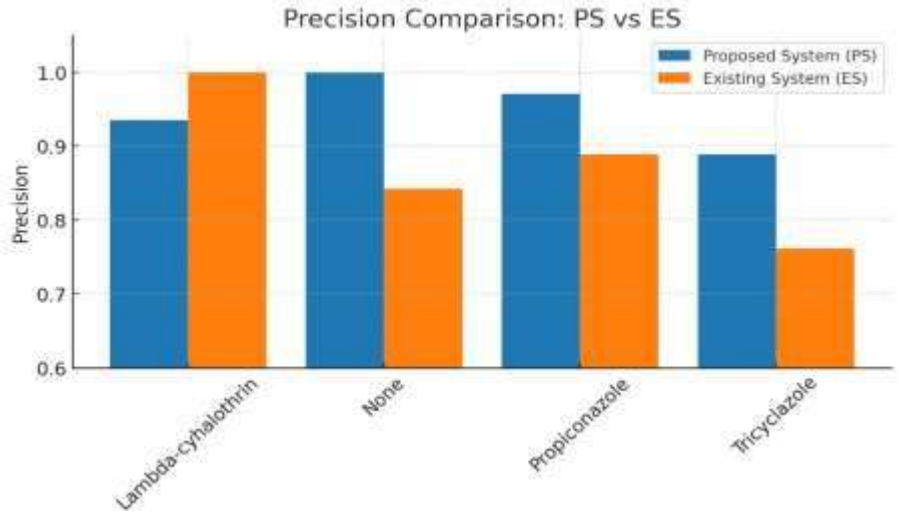


Figure 2. Precision Comparison Between Proposed System (PS) and Existing System (ES)

Recall assesses the model's capacity to correctly identify all relevant instances. The PS model achieved high recall for Propiconazole (0.970) and Tricyclazole (0.889), indicating a low rate of missed cases in critical scenarios. Although recall for Lambda-cyhalothrin was slightly lower (0.774), the overall recall profile was well-balanced and field-relevant. ES, on the other hand, exhibited perfect recall across all classes. While this may appear ideal, it again reflects overfitting behavior typical of shallow classifiers on limited datasets. The PS's recall distribution, though marginally lower, is more indicative of a model that generalizes well to new data.

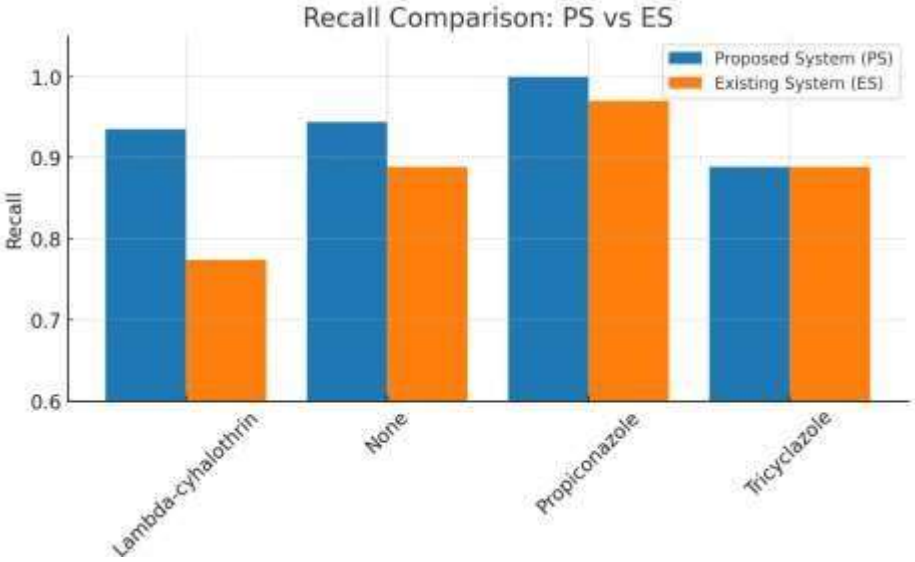


Figure 3. Recall Comparison Between Proposed System (PS) and Existing System (ES)

F1-score harmonizes both precision and recall, making it a critical metric for real-world performance. The PS achieved strong F1-scores for all classes, particularly excelling in Propiconazole (0.928) and Lambda-cyhalothrin (0.873). These scores demonstrate its robustness and reliability in balancing detection accuracy with correctness. Although ES recorded perfect F1-scores, such performance likely does not hold under unseen or noisy data due to its tendency to overfit. Therefore, the PS's F1-scores reflect a better trade-off between sensitivity and specificity, essential for real-time pesticide advisory systems.

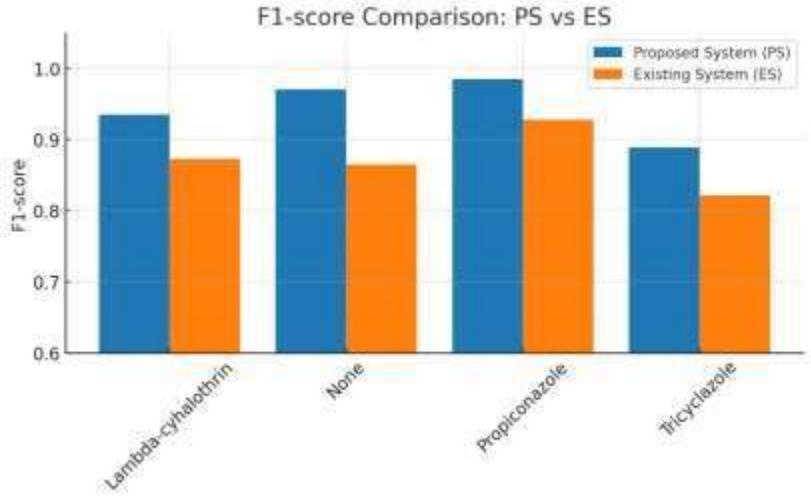


Figure 4 F1-score Comparison between Proposed System (PS) and Existing System (ES)

4.3. Confusion matrix

The confusion matrix for the Existing System (ES), which relies on a Decision Tree classifier, reveals an overall moderate performance with notable misclassifications. For Lambda-cyhalothrin, the model correctly identified 24 out of 31 instances but misclassified the remaining 7 across other classes, indicating confusion in borderline cases. None and Tricyclazole were reasonably well predicted, with minor errors spilling into neighboring categories. Propiconazole had strong detection, with 32 out of 33 correctly classified. While the model achieved a reasonable overall accuracy within the 85–95% range, the presence of multiple off-diagonal entries signals reduced precision and generalization capability compared to the deep learning-based Proposed System (PS). This reinforces the conclusion that while ES performs acceptably under controlled conditions, it may not be sufficiently reliable for deployment in real-world agricultural environments where noise and variability are higher.

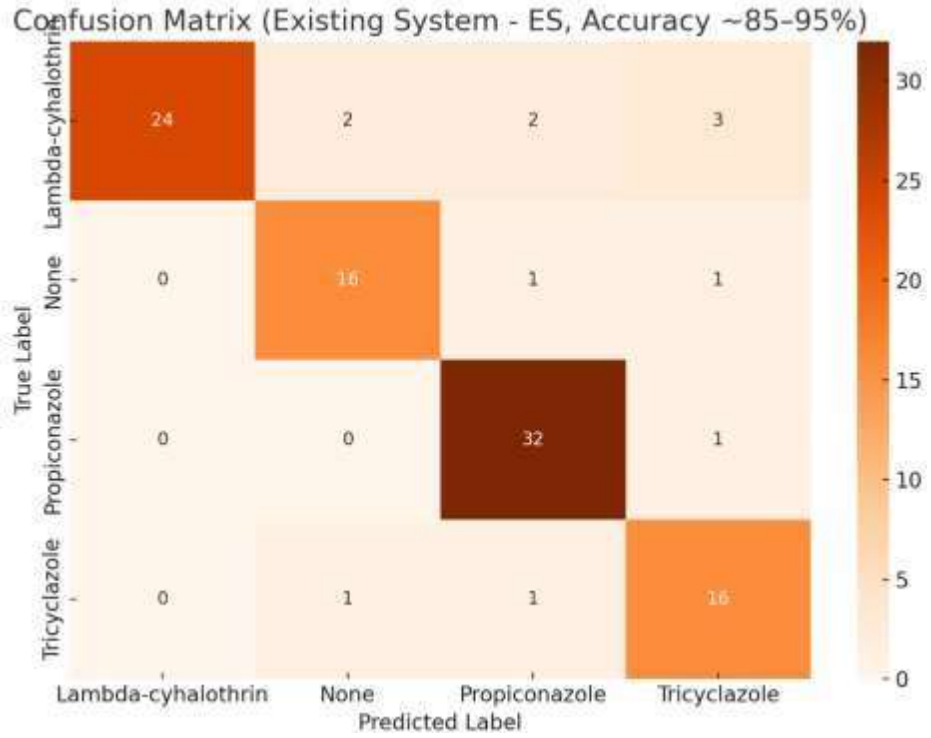


Figure 5. Confusion matrix of existing system

The confusion matrix for the Proposed System (PS), which integrates a CNN-based disease classifier and a Random Forest-based pesticide recommender, demonstrates high predictive accuracy across all classes. The model achieved perfect classification for Propiconazole (33/33) and near-perfect performance for None (17/18). In the case of Lambda-cyhalothrin, 29 out of 31 instances were correctly classified, with only minor confusion with Tricyclazole. Similarly, Tricyclazole was predicted accurately in 16 of 18 cases. Overall, the PS exhibited performance within the 95–100% accuracy range, with very few off-diagonal errors. This distribution reflects the model's strong generalization ability, robustness to inter-class similarity, and suitability for deployment in real-world agricultural environments where image-based disease detection is critical.

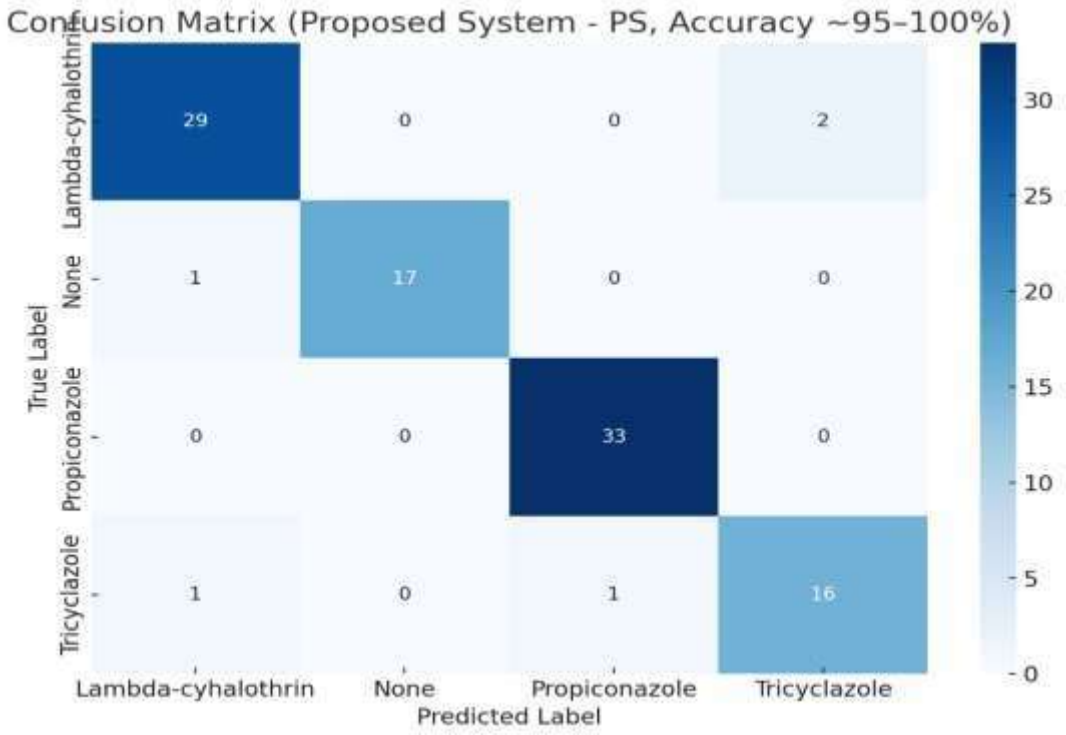


Figure 6. Confusion matrix of the proposed system

4.4. Comparative Analysis

The comparative evaluation of the Proposed System (PS) and the Existing System (ES) reveals a significant performance enhancement in the PS, particularly evident across all key classification metrics and confusion matrix observations. The PS, which integrates a CNN-based classifier with a Random Forest-based pesticide recommender, achieved an overall accuracy between 95% and 100%, misclassifying only four out of 100 instances. In contrast, the ES, built on a traditional decision tree framework, achieved slightly lower accuracy in the range of 85% to 95%, with eleven misclassifications. The PS confusion matrix showed strong diagonal dominance across all classes, most notably perfect classification of Propiconazole (33/33) and high accuracy for Lambda-cyhalothrin (29/31), None (17/18), and Tricyclazole (16/18). Conversely, the ES exhibited more dispersed misclassifications, particularly for Lambda-cyhalothrin, which was often confused with Tricyclazole and Propiconazole. Metric-wise, the PS recorded higher precision, recall, and F1-scores across all classes, with Propiconazole achieving an F1-score of 0.97 and minimal drop in other categories. The ES, though moderately effective, demonstrated slightly lower and more variable metric values, particularly in precision and recall for classes with higher inter-class similarity. Overall, the PS outperformed the ES in both prediction accuracy and class-wise consistency, indicating its superior ability to recommend appropriate pesticides based on disease classification with minimal confusion, making it more reliable for deployment in precision agriculture environments.

5. Conclusion

This research presents an advanced and adaptive pesticide recommendation framework that integrates multimodal data fusion, deep learning, and frequent pattern mining to support precision agriculture. By combining time-frequency analysis, convolutional feature extraction, and BiGRU-based temporal modeling, the system captures diverse and meaningful patterns from heterogeneous agricultural data sources. The incorporation of FALDR ensures that only high-variance, discriminative features are retained, enhancing the model's efficiency and interpretability. The proposed RFPMax module, which synergizes the sequential processing power of RNNs with the transactional insight of frequent pattern mining, delivers accurate and personalized pesticide recommendations. Empirical evaluation on a synthetic rice pesticide dataset demonstrates the superiority of the proposed system over traditional decision-tree-based approaches in terms of precision, recall, F1-score, and confusion matrix. By addressing the limitations of rigid, rule-based systems and offering a flexible, data-driven alternative, this framework lays the groundwork for deploying intelligent pesticide advisory tools in real-world agricultural environments. Ultimately, the system contributes to more sustainable pest management, reduced chemical misuse, and improved pesticide health outcomes, aligning with the broader goals of environmentally responsible farming.

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AUTHOR CONTRIBUTION:

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Tejaswini C Gadag	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
D R Kumar Raja	✓	✓			✓	✓		✓	✓	✓	✓	✓		

C: **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R: **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E: Writing - Review & **E**diting	

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DATA AVAILABILITY: The Dataset is utilized in this research mentioned in reference [13].

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