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Original Article

Enhancing Fertilization Strategies through Graph Attention Network - Transformer Fusion Model for Smart Farming

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Abstract - *India's GDP is driven by the agriculture sector, which provides numerous individuals with livelihoods. During harvest, climatic and weather conditions highly affect crop production, resulting in losses, and incorrect analysis of these factors can result in lower yields. A well-defined process is needed to develop a model keeping geographical diversity in mind while ensuring accurate, cost-effective fertilization methods. This study introduces a hybrid model by integrating Transformers with Graph Attention Networks (GAT) to estimate fertilizer needs based on the region's unique requirements. GATs identify spatial correlations by modelling farms as graph nodes and edges connected by geographic distance based on closeness. Transformers handle sequential data to reveal temporal patterns. The hybrid model successfully combines spatial-temporal data, identifying complex relationships to make specific fertilization recommendations dynamically. It surpasses conventional ML models' accuracy, scalability, and adaptability, delivering consistent outcomes in the analysis of Tamil Nadu and Punjab regions. As India's agriculture is diverse regarding soil types, climates, and agricultural practices, this adaptive method updates recommendations dynamically, improving precision and relevance for farmers.*

Keywords - *Precision farming, Fertilizer optimization, Machine learning, Hybrid models, Graph Neural Networks.*

1. Introduction

It is estimated that the world's population will rise by about 2 billion to 9.7 billion in the next 25 years [1]. Agriculture faces a dual challenge: to arrange for the world's increasing population's food security while not damaging the environment. It must, therefore, use modern technologies in agroecosystems to increase food supplies and minimize the adverse effects of chemical fertilizers and improper waste management [2]. Traditional farming in India relies on labor-intensive and environmentally sustainable practices, including crop rotation, agroforestry, and using natural manure for fertilization. While these methods promote soil health and sustainability, they require significant time for crop production and involve high input costs [3]. Plants need macro and micronutrients for optimal growth; fertilizer is the primary source of these micronutrients. They aid in plant growth and maintain soil fertility to ensure long-term agricultural productivity. The conventional use of fertilizers involves soil testing and choosing the appropriate fertilizer, either based on the plants' needs or the soil conditions. Other significant factors include applied methods, proper dosages, and proper timing to prevent over-fertilization [4]. Government agencies and policymakers have been keen to reduce the overuse of chemical fertilizers. However, the recent slowing in nitrogen use and reduced phosphorus and potash should be closely managed to maintain soil nutrient balance [5].

Climatic conditions, soil types, geography, land use, crop management, pedogenic processes, and physiographic factors influence the NWIH region's soil parameters. Knowledge of these impacts is vital for sustainable soil resource management and agriculture. Management zone maps are critical for optimizing agronomic inputs, especially fertilizers, to enhance environmental sustainability and economic efficiency [6]. The fertilization recommendations for paddy rice are uniform for all regions and not adjusted for variability in soil content of P and K. Information regarding the P and K nutritional levels of rice fields-defined as low, medium, or high-would be very helpful in developing such accurate, site-specific fertilizer recommendations [7].

Soils differ significantly from region to region in terms of nutrient content, pH, texture, and organic matter. A uniform approach to fertilization can prove inadequate since it either renders the soil deficient in nutrients or leads to overuse. For example, Punjab is rich in phosphorus but has a poor

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percentage of micronutrients like zinc and boron [8]. Rainfall and temperature vary with each region and are crucial in fertilizer effectiveness. Heavy rain can cause nutrient leakage, while drought conditions delay fertilizer absorption without adequate irrigation, underscoring the need for climate-adapted fertilization strategies [9]. Similarly, regional studies on wheat and maize crops show that local varieties may need custom fertilization strategies based on their genetic characteristics and the environment in which they are grown. In other areas, local crop rotation and organic fertilization could minimize the use of chemical fertilizers, while monocropping-intensive systems require more significant synthetic fertilizer inputs. This suggests the need to integrate the farming practices of a local region into the fertilizer optimization models for more sustainable agriculture production [10]. It is essential to address the issues of changing climatic conditions and regional variations regarding soil structure while devising an effective and efficient fertilization strategy.

Numerous studies on fertilization optimization neglect regional variations despite their essential significance in facilitating efficient and site-specific fertilizer management [11]. The requirements for fertilization are significantly different depending on the soil type, climate, crop variety, and local agricultural practices. This calls for recommendations on fertilizer to be made on a regional basis. Strategies for fertilization must be tailored to the regional variations in soil composition, climate, crop requirements, and practices**.** Existing models are mostly generalized and cannot adapt to localized conditions, which is crucial in regions with varying soil characteristics, such as western India. If this is not considered, it may result in inefficient use of fertilizers, environmental degradation, and low crop productivity.

This research addresses this critical gap by presenting a GAT-Transformer model combining spatial and temporal data to optimize fertilizer strategies, accounting for regional and environmental variations. This model efficiently captures regional differences through Graph Attention Networks for spatial relationships and through Transformers for the temporal trends to provide region-specific solutions toward a sustainable fertilizer. The GAT-Transformer hybrid model's ability to jointly learn spatial and temporal dependencies makes it adaptable to diverse agricultural challenges. It enables precise and sustainable fertilization strategies. The generated model is tested on the Punjab and Tamil Nadu regions and provides better results than existing studies.

2. Related Work

A detailed literature review was carried out researching advances related to Graph Neural Networks (GNNs) in agriculture, Transformer models for precision farming, Hybrid GNN and Transformer architectures, and deep learning-based optimization in fertilization. This study attempts to evaluate and identify the key techniques, current emerging trends, and applications developed for agriculture management, emphasizing optimal fertilizer management and dealing with regional variations.

Graph Neural Networks (GNNs) are specialized neural systems that use message transmission between nodes to capture dependencies in graph-structured data. GCN, GAT, and GRN are recent developments in GNN variations that have shown impressive performance in a range of deep learning tasks. This study [12] highlights the distinctive qualities and contributions of the main varieties of GNN models and presents a broad design framework for creating them. GNNs are utilized in precision agriculture to model spatial and temporal relationships between farm plots, crops, and environmental factors, enabling optimized decision-making for tasks like irrigation, fertilization, and yield prediction.

GNN and CNN-based models have been instrumental in advancing pest disease detection. A CNN-based pest detection system (GPA-Net), with a multilayer graph pyramid structure, trilinear attention module, and CSP backbone, was introduced to enhance pest detection. With up to 99% accuracy on cassava leaf and other datasets, it promotes smart agriculture and environmental protection [13]. In a related effort, the study [14] implemented knowledge graphs and DL for the sophisticated detection of plant diseases. However, these models need to be structurally optimized for practical application in intelligent agriculture and to extend beyond identifying pests and diseases to weather forecasting and managing grain storage. This can be solved by improving computational efficiency, fusing multi-domain datasets, and employing transfer learning methodologies. This study [17] demonstrates the pipeline for few-shot learning with Swin transformers to achieve very high accuracy for pest detection in scarce data conditions. It can differentiate between similar classes and localize symptoms using GradCAM. However, there is a scope to simplify models through feature distillation and venture toward OFSL to handle unreliable labels in limited datasets.

Multiple studies have focused on predicting yield and plating recommendations using GNN. This study [15] proposed a knowledge graph-based recommendation method for identifying appropriate maize planting areas using county-scale meteorological data. The model outperformed traditional machine learning and graph-based methods by improving recommendation accuracy by up to 24.3%. The study [16] introduces the ASTGNN model, which combines GNNs and attention mechanisms with varied geospatial data to predict wheat yields in Anhui, China, during winters with a high accuracy of $R^2 = 0.70$. The proposed model improves early yield forecasting and provides valuable insights for advancing digital agriculture and managing climate impacts. Integrating soil nutrient data with knowledge graphs and incorporating real-time climate factors can enhance fertilizer recommendation accuracy. A multimodal and temporal deep learning framework that integrates data from both perspectives is proposed: meta-transformers and temporal GNNs are combined to determine crop yield classifications [17]. This demonstrates the effectiveness of integrating geographical and temporal knowledge for yield predictions.

Fertilizer optimization is still underappreciated despite significant advancements in yield and pest modelling. In [18], the authors developed a Q-learning-based simulation tool to optimize fertilizer application dynamically using real-time environmental and remote sensing data for observing crop growth and quality. The framework implemented a reward-based mechanism for deciding on the optimum nourishment level. Experimental results have established the computational efficiency of the approach and indicate its performance to be at par with or even superior to advanced deep learning models. However, the approach doesn’t consider regional variations and may not be adaptable. The NDCF system proposed to optimize fertilizer recommendations by integrating properties of soil and nutrients, as introduced in this research. It captures both linear and nonlinear land-nutrient interactions using WMF and FC-MLP, thus bringing a 1.44% enhancement in accuracy over baseline methods [19]. A possible future direction could be further improvement by using attention mechanisms for location-specific recommendations.

Additional studies developed mobile applications integrating multiple features. This study [20] introduces an agronomic aid system leveraging image processing, ML, and DL for features like disease identification in plants, weather forecasting, and a crop-specific fertilizer calculator. The app supports multilingual functionality in Marathi, Hindi, Punjabi, and English. The approach is limited by the dataset's lack of diversity in crop types and illnesses, which limits the algorithm's capacity to adjust to conditions in real-time and offer more exhaustive coverage. Irrigreat [21] provides a solution by offering neutral advice on biological and conservative fertilizers, helping agriculturalists make well-versed decisions for optimal crop growth. The research utilizes data science methods; a machine learning model achieves 96.44% accuracy, higher than the set target of 90%. A deep learning model is also integrated for pesticide recommendations based on pest identification. The app's crop-specific fertilizer calculator isn't very useful for site-specific fertilization methods because it doesn't have precision nutrient analysis, real-time weather integration, or dynamic soil data. This highlights how the system's capacity to offer accurate and flexible agronomic suggestions is restricted by the absence of soil and climate data integration.

Various models developed for fertilization rely on image-based inputs. This study [22] provides a YOLOv5 model-based target-oriented spray control system for cabbage fields that is enhanced with a transformer module for precise identification in challenging circumstances. A system based on the NVIDIA Jetson Xavier NX achieves 96.14% precision while processing images in 51.07 milliseconds. This study [23] uses a CNN model that combines XGBoost and PCC to discover key variables. Although promising, these techniques frequently suffer in dimly illuminated or obscured environments, compromising the dependability of real-world deployments. These findings show an over-reliance on image-based analysis, which reduces the reliability of disease detection in real-world settings by making it less effective under low light or obscured conditions.

Recent work has explored integrating transformers and optimization algorithms. This study [24] provides substantial technological assistance for improving nitrogen and maintaining superior tea-making control. With an accuracy of 92-96%, a ResNet-18 model accurately identified the nitrogen levels in tea granules and the buds. This study [25] proposes a Bagged Convolutional Neural Network (CNN) combined with the WOA to forecast rice production using a soil nutrient dataset with over 11,000 samples. The model uses CNN layers to process multidimensional numerical data. WOA optimizes weights, improving accuracy to 90.31% with an error rate of 9.69%.

This demonstrates that while Graph Neural Networks and Transformer models have been widely employed in PA for crop monitoring, pest identification, and yield prediction, the potential for fertilizer optimization in the above-mentioned models remains untapped. The presented research aims to overcome this constraint by proposing a novel fusion model that combines GATs and Transformers in a framework designed explicitly for fertilizer optimization. The proposed model uses GATs' relationship learning skills to examine spatial and soil nutrient interdependence, whilst Transformers improve temporal and contextual knowledge of agricultural data. The experimental results show that this fusion model is highly adaptable across different geographies, providing a scalable and effective strategy for increasing agricultural output and sustainability. The proposed GAT-Transformer fusion model offers a promising approach to closing gaps in fertilizer recommendation and sustainable farming.

3. Materials and Methods

Soil degradation, which is caused by the excessive use of fertilizers such as urea, is a significant problem in India, causing imbalances in soil health, reduced fertility, and environmental pollution. The excessive use of chemical fertilizers upsets the natural nutrient balance, leading to soil degradation and water pollution. India has 15 distinct agro-climatic zones [26], as shown in Figure 1, each with its soil types, climates, and crop requirements. This diversity requires a region-specific strategy of fertilizing crops for high productivity and optimal management of healthy soils.

Most Indian farmers have small landholdings, which puts them in a difficult situation because they have few resources.

It is critical to provide cost-effective solutions that can be scaled and enable optimization in terms of irrigation, fertilization, and pesticides. The SHC Scheme [27] is a government initiative that promotes organic farming and fertilizer balance. Sustainability must be included in farming techniques and regional strategies to overcome these concerns. These challenges can be addressed by implementing an optimized fertilization model that promotes balanced nutrient application. This study is envisioned to capture regional variations in soil and environment data for fertilizer application. It has been tested on two different Indian states, Punjab and Tamil Nadu, with unique agricultural characteristics. Punjab follows irrigation-intensive monoculture farming, has loamy soil, and relies heavily on fertilizers for wheat and rice cultivation. In contrast, Tamil Nadu's rain-fed, diversified agriculture, with moderate fertilizer use, supports crops like paddy, cotton, and groundnut, with varying soil types and irrigation from the Kaveri River.

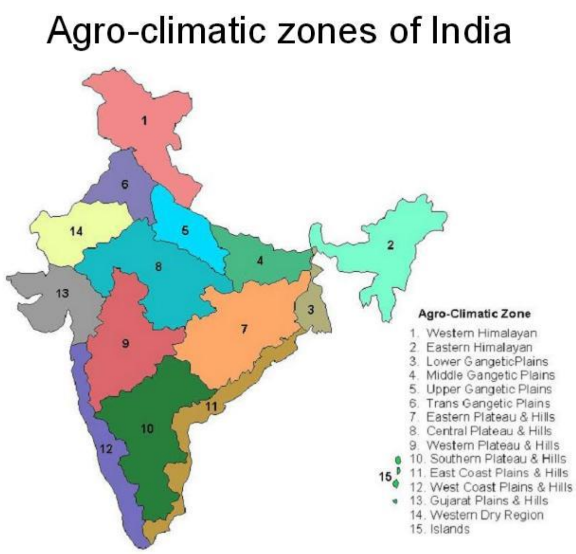

Fig. 1 Agro-climatic Zones of India

GAT and Transformers are combined to prepare a fusion model to recommend optimized fertilization, considering spatial and temporal data. All types of agricultural data are collected from different sources and normalized. The GAT layer captures the spatial dependencies by assigning weights to close farmlands based on similarity, and seasonal variations are captured by the transformer model. The outputs from both layers are combined to devise and generate a precise region-specific strategy for fertilization recommendation. This approach promises to ensure a complete understanding of dynamic agricultural data and has better decision-making capabilities.

3.1. Data Collection and Types of Data

Crop growth trends, weather and climate records, soil nutrient maps, and geospatial data are some of the data sources used in this study. The dataset is intended to include region-specific data on agricultural practices, climate, and soil characteristics. Processing of data before analysis helped to remove inconsistencies and missing values. Missing data points are filled using an Expectation Maximization approach, which calculates the mean of existing values for replacement. To ensure uniformity, the dataset is normalized so that all attributes are on the same scale for effective modelling and analysis.

Nutrient data for soils is accessed from the SHC [36] website and the Nutrient Dashboard offers data on macronutrients and micronutrients at the state level. Weather and climate data, temperature, rainfall, and humidity are available from the India Meteorological Department (IMD) [28] through its Climate Data Service Portal, and the All India Seasonal and Annual Temperature Series are available on data.gov.in [29].

Data on crop growth stages is not readily available. Still, the Soil and Land Use Survey of India [30] gives information regarding land use patterns and soil health, which can correlate with crop growth. The Bhuvan platform [31], hosted by the National Remote Sensing Centre, is used for geospatial data, including latitude, longitude, and adjacency status of farmlands. These diverse datasets are integrated to construct a comprehensive GNN model tailored to India's agricultural landscape to enhance fertilization strategies through informed decision-making. The main goal of fertilizer optimization is to estimate the optimal amount required for NPK. The final attribute list reflected and used in the study is presented in Table 1.

Table 1. Types of data

Type of Data	List of Attributes
Soil Nutrient Maps	Nitrogen, Phosphorus, Potassium, and Organic Carbon levels
Weather and Climate Data	Temperature (°C), Rainfall (mm), and Humidity (%) for each data point.
Crop-specific Growth Patterns	Early, Mid, and Late Growth stages
Geospatial Data	Latitude, Longitude, and Adjacency status of farmlands

3.2. Graph Attention Networks

GNNs are highly effective models for explaining graph-oriented data because they capture links and interactions via messages delivered between nodes. A primary use is node classification, which uses labels for some nodes to predict labels for others without ground truth. GNNs and Convolutional Neural Networks (CNNs) differ significantly in pipeline design, loss functions, computational techniques, and implementation tactics. GNNs iteratively aggregate and transform information from connected neighbors. Each node updates its representation by combining its features with those of its neighbors through neural network layers.

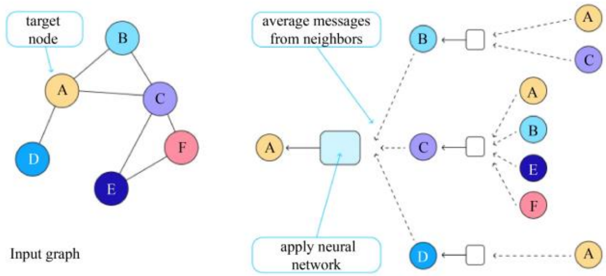

Fig. 2 Input graph and GNN Working [32]

Thus, GNNs can easily capture complex spatial dependencies, making them suitable for fertilizer optimization applications in agriculture. The working of GNN and the Graph structure is shown in Figure 2.

This study's primary goal is to forecast the ideal fertilization range while considering regional variances. GAT is a type of GNN that appears to be an appropriate choice. GATs dynamically assign weights to nodes and edges based on their importance. Here, a graph-based representation is applied where nodes (vertices) refer to farmlands, basically, districts in a state, and edges represent relationships between such regions based on geographic proximity. Each node contains node features with more elaborate information about the soil pH level, nutrient availability, and the crop mainly cultivated in that area. The edges are enriched with edge features that encode the relationships' precise nature, like whether two regions are adjacent or not and up to which degree the similarity in temperature and rainfall trends exists. This design provides a detailed and comprehensive model for farmlands and their interactions.

3.2.1. Graph Notation

The representation of a graph is Graph (V1, E1), where V1 represents farmlands, E1 represents relationships between regions, Node attributes are represented, including soil, weather, crop, and geospatial data, and Edge weights are defined as capturing proximity or similarity metrics. Each node in the graph represents a farmland and is characterized by a feature vector containing soil nutrients and geospatial coordinates specified by latitude and longitude. These features comprehensively describe each farmland's characteristics, allowing detailed analysis and prediction. Each edge in the graph is defined by features, including weights representing specific relationships between adjacent nodes based on past patterns. Adjacency is binary, with 1 representing adjacent farmlands and 0 representing no direct connection. In addition, soil similarity is treated as a continuous value (e.g., 0.8), representing the degree of similarity in soil properties between adjacent nodes. An attention mechanism is used to learn dynamic weights for the edges. The model concentrates on the most pertinent connections for learning since attention scores are calculated for each edge according to the predefined weights and the node attributes of the connected nodes (u and v). Edge weights are dynamically adjusted, and a graph reduction step removes unimportant edges, reducing noise in the learning process.

3.2.2. Feature Transformation

Before computing attention, the raw feature vectors of the nodes are linearly transformed into a new representation space using a learnable weight matrix W. This transformation, as represented in equation 1, ensures that the features are compatible with subsequent attention computations.

$$h'_u = W.h_u \tag{1}$$

Where $h_u$the feature of node u and W is the weight matrix, the transformed feature h'_u is then used for the attention calculation.

3.2.3. Attention Coefficients

The attention mechanism determines the importance of each neighboring node v for a target node u with equation 2. The modified characteristics of connected nodes and any edge attributes are used to compute attention scores for every edge (u, v).

$$\alpha_{u,v} = \frac{\exp(LeakyReLU(a^T[h\prime_u||h\prime_v||e_{u,v}]))}{\sum_{k\in N(u)}\exp(LeakyReLU(a^T[h\prime_u||h\prime_k||e_{u,k}]))} \tag{2}$$

Where,
a - is a learnable attention vector.
|| - denotes concatenation
$e_{u,v}$ - is the edge feature

A learnable attention vector ‘a’ is applied to ascertain each feature's contribution to the concatenation, letting the model concentrate on crucial elements of the edge and node characteristics. The nonlinear activation function LeakyReLU is applied to the weighted features, introducing nonlinearity to assist the model in capturing complicated relationships within the graph. Finally, Softmax normalization ensures that the attention scores $\alpha_{u,v}$ for all neighbors v∈N (u) sum to 1, enabling the model to distribute focus among the neighbors during feature aggregation proportionally.

3.2.4. Feature Aggregation

Once the attention scores $\alpha_{u,v}$ are computed, the features of the nearby nodes are combined to update the target node’s (u) feature representation. Each neighbor’s contribution is weighted by its attention score, as shown in Equation 3.

$$h'_u = \sigma\left(\sum_{v\in N(u)}\alpha_{u,v}.W.h_v\right) \tag{3}$$

Where,
$W.$: The transformed feature vector of the neighbor node v is projected into the same space h_u.
$\alpha_{u,v}$**:** The attention score, indicating how much influence v's features have on u.

σ: ReLU, used on aggregated features to introduce nonlinearity and capture more complex patterns

3.2.5. Multi-Head Attention(MHA)

Varied associations are recorded using MHA to improve the model's learning ability. Rather than a single attention mechanism, numerous separate attention heads are used. Each head learns a different set of attention scores and aggregates features uniquely.

3.3. Transformers Model

Transformers are highly effective for learning temporal patterns in sequential data. Once the spatial dependencies are captured, the enriched feature matrix is passed to the transformer to model temporal relationships (growth stages and climatic conditions over time). The transformer employs self-attention processes to learn the relationships between distinct time steps.

3.3.1. Scaled Dot Product Attentions

Each input feature is linearly transformed into three separate matrices: Query (Q), Key (K), and Value (V) using equation 4. These transformations are learned parameters that let the model focus on certain relationships. The attention mechanism computes scores between queries and keys using the scaled dot product:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

Where
d_k - Dimension of key vectors
QK^T - Computes the similarity between the Q and K.
Softmax - converts the similarity scores into a probability distribution, emphasizing essential connections.
V is the values weighted according to the calculated attention scores.

This [33] mechanism determines the importance of each time step relative to others by calculating attention scores and weighting V values accordingly.

3.3.2. Multi-head Attention (MHA)

In MHA, multiple attention mechanisms operate simultaneously and independently. Each attention head computes its own Q, K, and V matrices by applying separate linear transformations to the input, as shown in Equation 5. By combining the outputs from all heads, the model achieves a richer and more comprehensive representation of the input, enhancing its ability to learn complex patterns effectively.

$$MultiHead(Q,K,V) = Concat(head_1, \dots \dots, head_n)W^0 \tag{5}$$

Where
$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$ for each attention head
W^0 is a learnable output weight matrix

3.3.3. Transformer Layer Output

$$\text{Output=Norm(X+ AttentionOutput)} \tag{6}$$

Where
Attention Output is $MultiHead(Q,K,V,)$ and X is input to the transformer layer.

The training is stabilized by merging input X with the output from multi-head attention and normalized using layer normalization. This results in a temporal representation that effectively captures the evolution of dynamic factors with respect to time. The dynamic factors include climate changes, crop growth stages and soil characteristics.

3.4. The Fusion Layer

Combining these two architecture models enables the hybrid model to join insights related to latitude and temporal factors to synthesize a comprehensive understanding of the interaction between different fields and their temporal variability, represented using equation 7. This is applied in the present study to forecast optimal fertilization needs based on spatial relationships and temporal variations in climatic and agricultural conditions. This combination enables the model to effectively assimilate local (GAT) and global (Transformer) connections.

$$F_{hybrid} = \sigma(W_{gat}H_{gat}(K) + W_{trans}Z_t + b) \tag{7}$$

Where
W_{gat}: are learnable weights for the GAT output
This represents the output from the Graph Attention Network after K layers
W_{trans}: is the weight matrix for the Transformer's output at time step t
b: represents a bias term.

The self-learning fusion layer dynamically balances GAT and Transformer contributions, while uncertainty quantification estimates confidence levels for fertilizer predictions.

3.5. Uncertainty Quantification

Uncertainty quantification provides a measure of confidence in the fertilizer predictions generated by the model. By quantifying uncertainty, the model can indicate when predictions are highly confident or when caution is needed due to uncertain data conditions. This helps farmers make decisions, reducing the risk of over- or under-fertilization, resulting in better crop yield and sustainable resource utilization. This is especially useful in agriculture, where decisions must consider variability and risk. The model is designed to predict two outputs for each input:

a) Mean (μ): The expected value of the fertilizer requirement.

b) Variance (σ^2): The uncertainty or confidence interval around the predicted mean.

Mathematically, the model outputs:

$$\text{Prediction}=FC_{\mu}\left(F_{hybrid}\right)$$
$$\text{Uncertainty}= FC_{\sigma^2}\left(F_{hybrid}\right)$$

Where F_{hybrid} represents the fused feature representation from the hybrid model.

3.6. The Model Training and Evaluation

Processing the graph (G) and temporal data is the model's initial training and assessment stage. The Transformer analyses the temporal data to capture sequential dependencies, while GAT processes the graph to model spatial interactions during the forward pass. The outputs from both components are then fused into a single representation. A combined loss function (L) is used for training, and terms of Huber Loss and uncertainty regularization are monitored. The model outputs the predicted mean (μ) and the variance (σ2) during inference. Confidence intervals are then computed using the variance, giving a range that the actual value is anticipated to fall inside with a given degree of confidence. For example, a 95% confidence interval can be computed as:

$$Confidence\ interval = \mu \pm z.\sqrt{\sigma^2} \qquad (8)$$

Where z is the z-score corresponding to the desired confidence level, this quantifies the model's uncertainty, offering actionable insights for decision-making.

The model is evaluated using weights trained with Adam on a separate test set. Metrics, MAE, RMSE, and Uncertainty Calibration Error are computed to assess accuracy and reliability. The model is tested across two locations and crop types to ensure good generalization. Figure 3 depicts the system's workflow. The outputs from the GAT, capturing spatial relationships between fields, and the Transformer, modelling temporal dynamics like climate changes, are combined to predict optimal fertilization ranges for each field. This hybrid approach considers inter-field influences and time-dependent factors, providing a comprehensive solution for precision agriculture. This model introduces several novel advancements that enhance its effectiveness. Dynamic edge weighting enables better representation of relationships between farmlands by adjusting edge importance in real-time. Hierarchical and adaptive feature aggregation improves learning by allowing the model to prioritize relevant features at different levels of granularity. Multi-resolution embedding captures local and global patterns, enhancing the model’s understanding of spatial and temporal dependencies. Additionally, self-learning fusion dynamically balances spatial and temporal contributions, ensuring optimal decision-making without manual tuning. Finally, the model integrates Transparency and uncertainty estimation, making predictions more interpretable and reliable for agricultural systems.

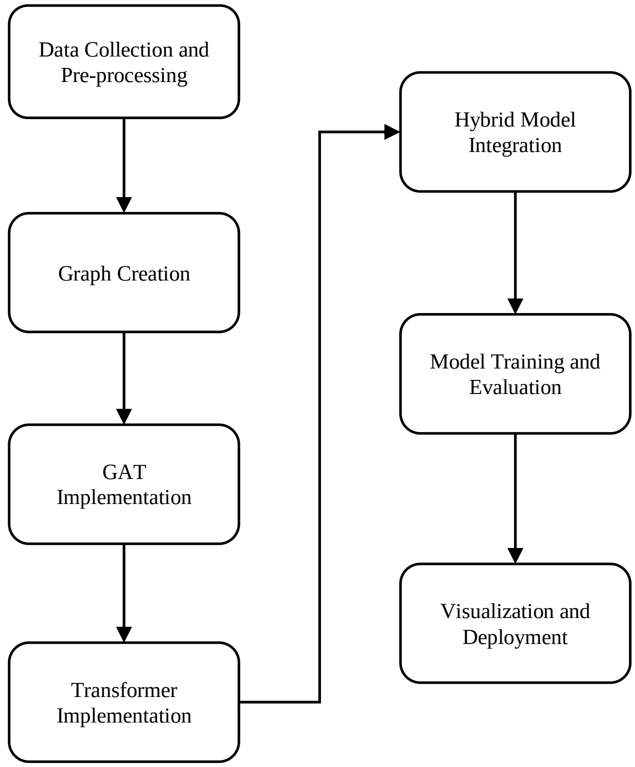

Fig. 3 Workflow of framework

4. Results and Discussion

Because of their distinct agricultural features, Punjab and Tamil Nadu offer a suitable basis for evaluating the model's ability to consider regional variations of farm data for fertilizer optimization. Punjab, located in North India, is known for large-scale wheat and rice farming. It relies heavily on irrigation from the Indus River and benefits from fertile, loamy soil, which supports high crop yields. However, intensive monoculture farming and high-intensity cultivation practices have raised concerns about long-term soil health. Fertilizer usage in Punjab is significantly high, with large amounts of nitrogen, phosphorus, and potassium applied to sustain productivity in its irrigation-dependent systems. Figure 4 shows the soil nutrients map of Punjab.

In contrast, Tamil Nadu, situated in South India, features a more diverse agricultural landscape, cultivating crops such as paddy, cotton, and groundnuts. Varied soil types, including red and black soils, support the state’s agriculture. It employs rain-fed and irrigated farming systems, often relying on the Kaveri River. Fertilizer use in Tamil Nadu is more moderate than in Punjab, emphasising tailoring inputs to specific crops and addressing regional soil deficiencies through micronutrient management. The contrasting agricultural systems, soil types, and climatic conditions between Punjab and Tamil Nadu provide a robust framework for testing the model’s adaptability to varying agricultural parameters, ensuring its effectiveness across diverse farming contexts. The soil nutrients map of Tamil Nadu is displayed in Figure 5.

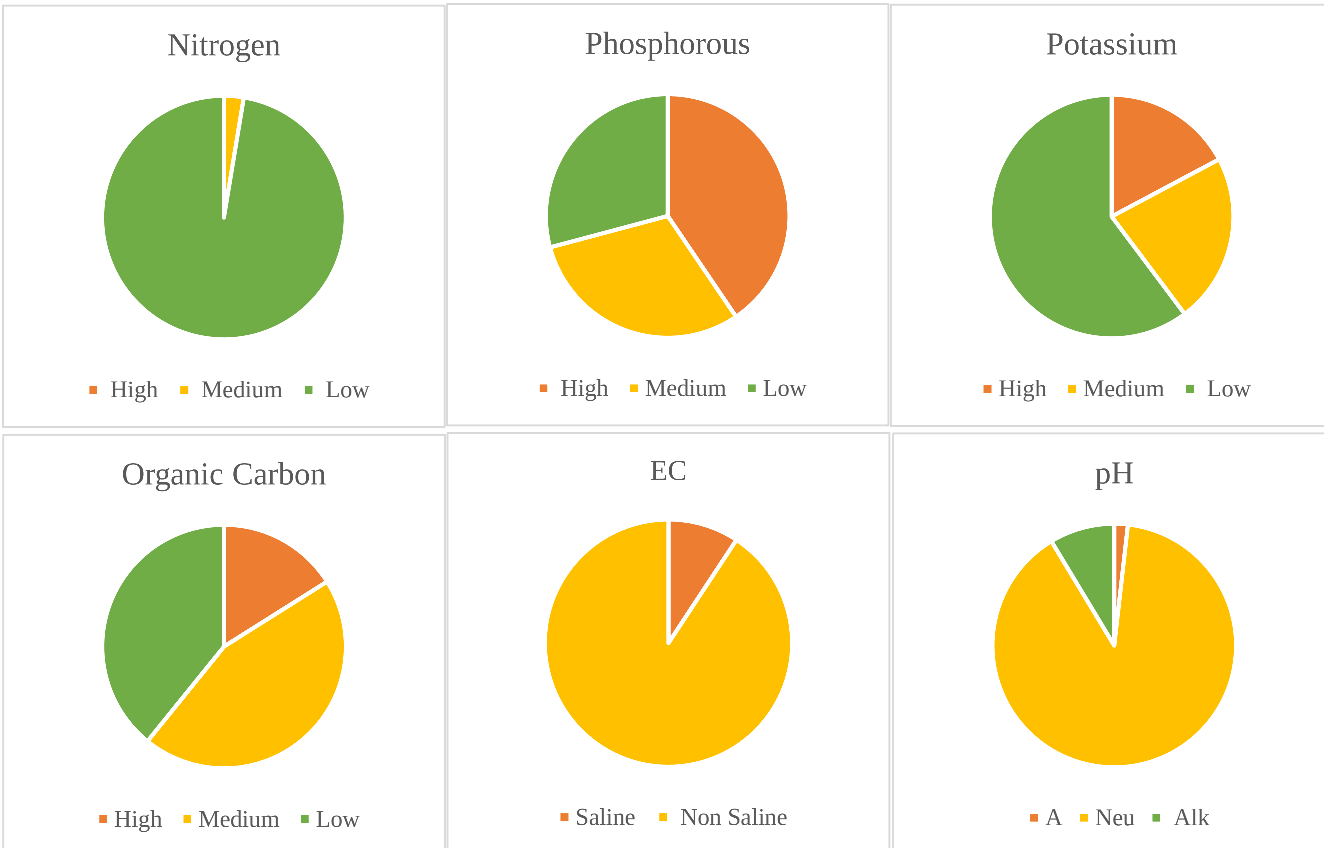

Fig. 4 Soil nutrients map of Punjab (micronutrients)

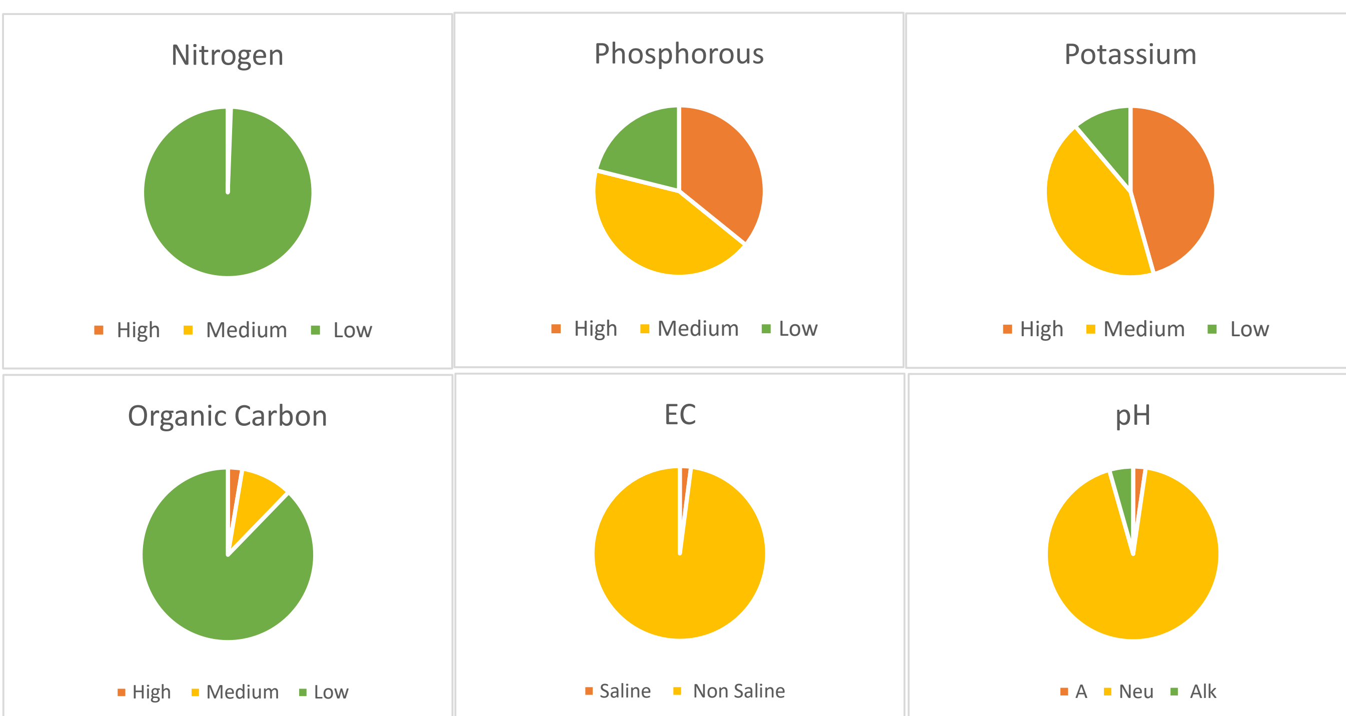

Fig. 5 Soil nutrients map of Tamil Nadu

Both soil maps, which are for 2024-2025, demonstrate the regions' diversity. Data is divided into spatial and temporal data. Each dataset is separately designed for Punjab and Tamil Nadu. The dataset includes various attributes, such as district, which represents the name or identifier of the district where data is collected. Soil nutrient levels are measured across different ranges: Nitrogen, Phosphorus, and Potassium in high, medium, and low ranges. Organic Carbon (OC) levels are high, medium, or low. The dataset also includes Latitude and Longitude, representing the geographical coordinates of the district's central point or sampling location. The longitude and latitude information is collected from [34].

The temporal data for the study is collected from [35], which consists of temperature, humidity, wind speed, and rainfall. The crop data and growth stages are collected from [36]. The GAT Transformer model was developed considering these datasets and was first trained on the Tamil Nadu dataset.

The graph is built using the attention mechanism, whereas the adjacency matrix is used to decide the edges of the nodes. The graph structure generated for Tamil Nadu is represented in Figure 6.

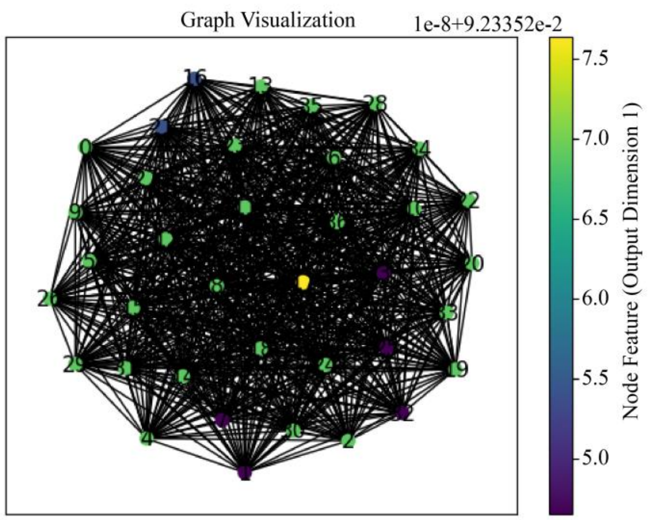

Fig. 6 Graph representation of Tamil Nadu

The graph is highly connected, meaning each node has multiple neighbours influencing it. It suggests strong interdependence between regions. The feature distribution, represented by a colour gradient, highlights bright yellow nodes with the highest feature values and dark purple nodes with the lowest.

This variation suggests that the GAT model has assigned different feature values based on learned relationships. The node labels, which correspond to the district, indicate that Node 16 (blue), which represents the TUTICORIN district, and one bright yellow node, seven, which represents the ERODE district in the centre, are key nodes in the network.

Since GAT applies attention mechanisms, some nodes receive more influence from their neighbours, making the yellow-highlighted node potentially a highly influential district, possibly due to central positioning or extreme soil properties. The dense connectivity of the graph implies that the model may be leveraging non-local interactions rather than just spatial adjacency, making it essential to check edge weights or attention scores to determine the most significant relationships. The graph shows that the yellow nodes indicate areas with higher fertilizer demand, while regions with similar colours likely share identical soil and weather conditions. Figure 7 shows the correlation matrix of GAT Output for the state of Tamil Nadu. The similarity matrix in GAT embedding aids in capturing the relationships between nodes based on their learned attributes. Figure 8 shows the similarity matrix of GAT output embeddings.

The GAT output correlation matrix reveals how different features interact after message passing, reflecting the model's learned relationships. Clusters of red blocks indicate strongly related features, while blue regions highlight opposing trends. A strong negative correlation suggests that one feature corresponds to higher fertilizer demand while another indicates a lower need in complementary conditions. This heat map represents a similarity matrix showing GAT output embedding, where the X and Y axes (1–36) correspond to different districts of Tamil Nadu.

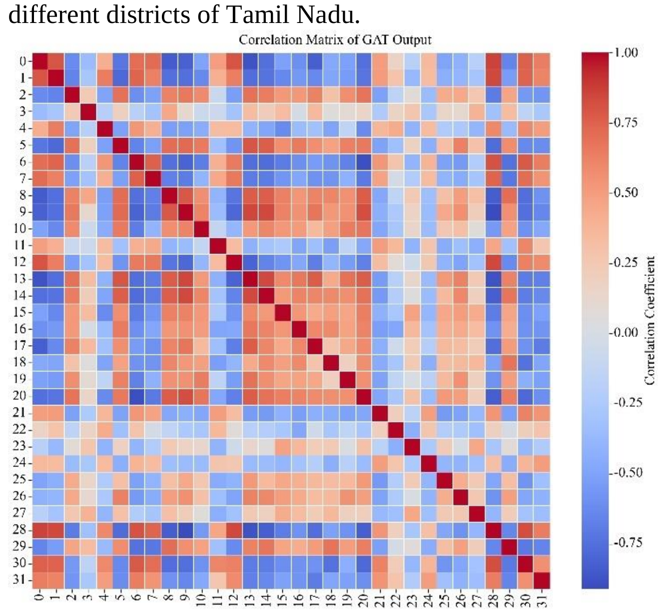

Fig. 7 Correlation matrix of GAT Output for the state of Tamil Nadu

The color scale indicates cosine similarity, with yellow (~1.0) showing high similarity, green (~0.0 to -0.4) indicating moderate similarity, and blue/purple (-0.8 to -1.6) representing dissimilar embedding. Diagonal yellow blocks (i, i) confirm self-similarity, while clustered green regions suggest the model has learned meaningful spatial relationships based on soil and adjacency features. Blue/purple patches highlight distinct nodes, likely due to differing soil nutrients.

Well-defined clusters indicate that the GAT layer effectively captures spatial and feature-based dependencies, while sparse dark patches suggest significant feature differences among specific nodes.

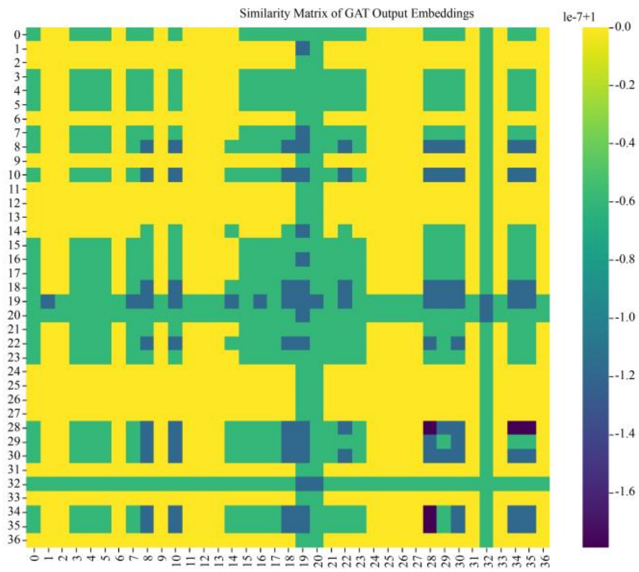

Fig. 8 Similarity matrix

The temporal data is analyzed using the Transformer model, which is trained separately on the Tamil Nadu dataset and assessed with performance metrics. Agro-climatic zones in Tamil Nadu [37] and crop production are available. The fertilization prediction is performed using a transformer model, and the results from the two models are combined to make the final predictions using the fusion model.

The fusion model runs for 100 epochs using MSE loss and Adam optimizer, storing loss values for visualization. Finally, the model is evaluated using MAE and MSE, and a loss curve is plotted to monitor training performance. The model achieved an MAE of 4.0952 and an MSE of 144.5147, indicating high accuracy and minimal prediction deviation. Figure 9 shows the Loss Curve for the Tamil Nadu region data.

The model utilizes specific hyperparameters across its GAT, Transformer, and Training components. In the GAT, the input dimension is determined by soil and spatial data concatenation. In contrast, the hidden dimension is set to 16 and the output dimension to 8. The edge dimension is 2, representing edge attributes, and self-loops are not included in the GATConv layer.

The Transformer module has an input dimension of 8 (matching the GAT output), a hidden dimension of 16 for feed-forward layers, two attention heads, and two encoder layers, with batch-first processing enabled. The model employs the Adam optimizer with 0.001 LR and MSE as the loss function for training. Training runs for 100 epochs, with target values initialized randomly in the shape of (n_nodes, 1).

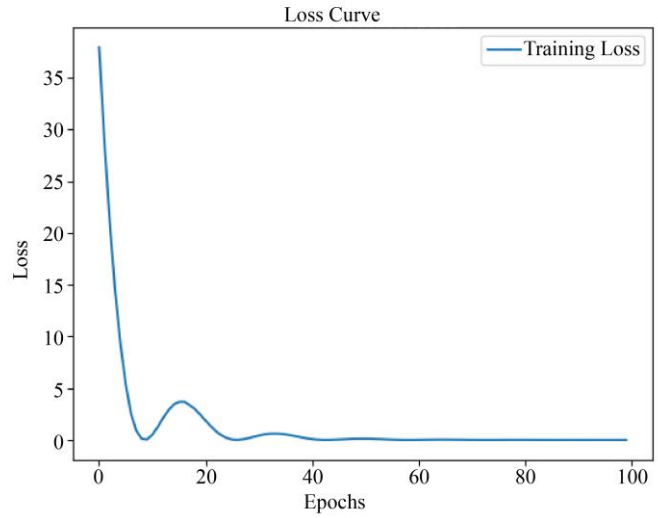

Fig. 9 The loss curve for Tamil Nadu

Key hyperparameters are tuned across GAT and Transformer during training to optimize the performance. The number of hidden units and attention heads for GAT are adjusted to enhance feature extraction. In the Transformer component, the number of layers, attention heads, and hidden dimension is optimized to improve representation learning. Fine-tuning is done by varying the LR, batch size and epochs. This comprehensive tuning approach ensures the best performance for the hybrid GAT-Transformer model. Table 2 shows the results of hyperparameter tuning.

Table 2. Hyper parameter tuning

Configuration	MAE Score
GAT(16, 2 heads) + Transformer(2 layers, 2 heads, 32 hidden) + LR=0.01	0.245
GAT(16, 4 heads) + Transformer(3 layers, 2 heads, 32 hidden) + LR=0.001	0.198
GAT(32, 2 heads) + Transformer(2 layers, 4 heads, 64 hidden) + LR=0.005	0.152
GAT(8, 1 head) + Transformer(1 layer, 2 heads, 16 hidden) + LR=0.01	0.312
GAT(32, 4 heads) + Transformer(3 layers, 4 heads, 64 hidden) + LR=0.001	0.174

More attention heads in GAT and Transformer improved performance, with four heads achieving the best results. Increasing hidden dimensions (16 → 64) reduced MAE, and an optimal learning rate (0.005) balanced training speed and accuracy, while excessive Transformer layers led to overfitting. The GAT (32 hidden, four heads) + Transformer (2 layers, four heads, 64 hidden) with LR 0.005 achieved a final MAE of 0.152 after 100 epochs.

The model is further trained on the Punjab dataset to assess the model's ability to generalize across regions. Figure 10 shows the graph representation of Punjab districts based on attention. Bright yellow nodes represent the fertilizer to indicate areas with higher fertilizer demand, while dark purple nodes may suggest regions with lower fertilizer requirements, as discussed in Tamil Nadu.

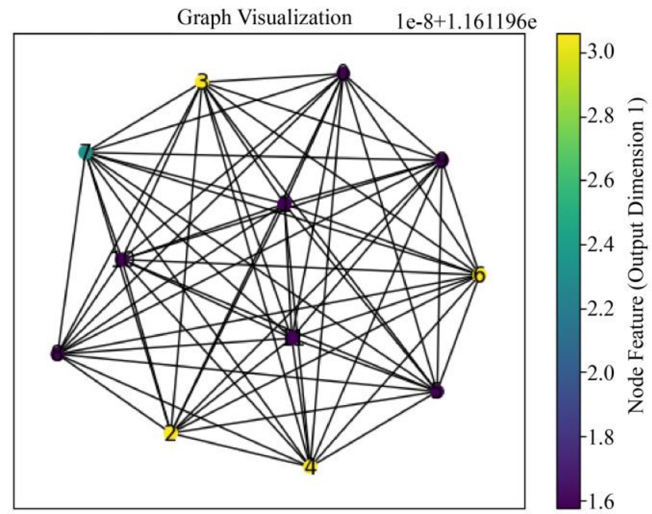

Fig. 10 Graph representation of Punjab

Figure 11 shows the similarity matrix of GAT Embedding.

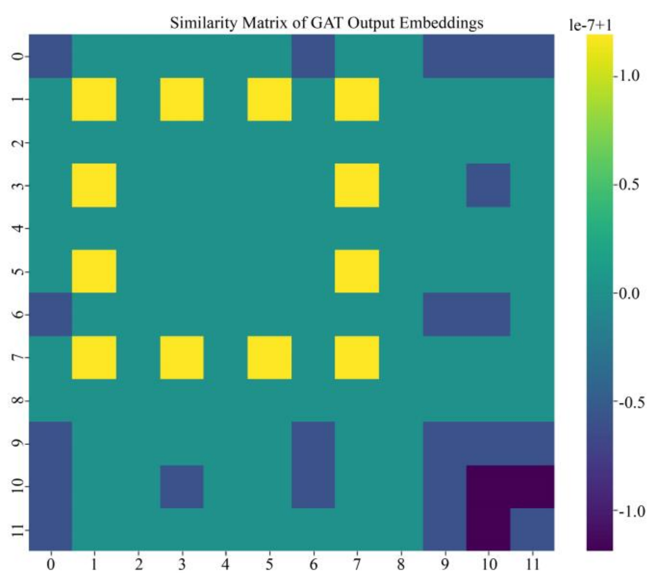

Fig. 11 GAT Embedding of Punjab District

Finally, the original hybrid model resulted in an MAE of approximately 8.22, and the Mean Squared Error (MSE) is approximately 529.63. In contrast, the hyper-tuned model resulted in an MAE of 2.78, similar to the MAE Given in the Tamil Nadu data, proving that the model is unaffected by regional variations. Figure 12 shows the loss curve for Punjab data. Trans-regional evaluation has helped to understand how well the model can predict fertilization requirements and crop yields in different environmental conditions and management practices, providing insights into its robustness and adaptability. The model has given similar results for data from the state of Punjab.

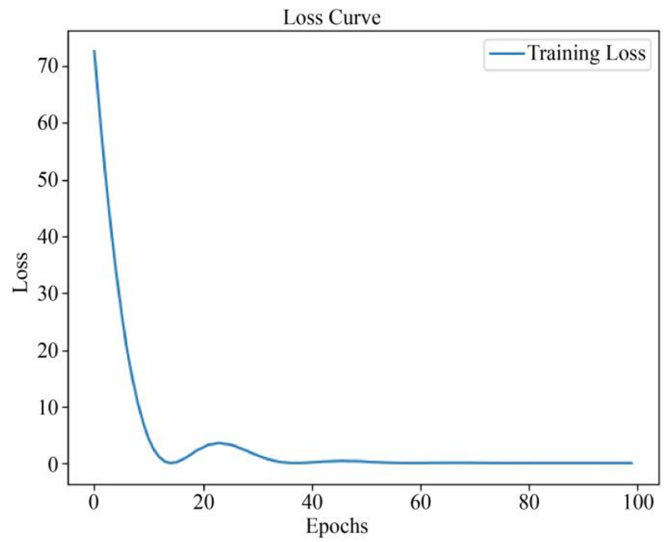

Fig. 12 Loss curve for Punjab

The suggested GAT-Transformer model is compared to ML models and CNNs for benchmarking, focusing on demonstrating its superior ability to optimize fertilizer use.

Conventional ML models, including Decision Trees, Random Forest, and XGBoost, are geared toward structured tabular data and not spatial information, which disadvantages them in their ability to leverage regional patterns within soil and weather conditions.

Moreover, they fail to consider spatial relationships among agricultural areas, resulting in generalized and less accurate fertilizer recommendations. Conversely, CNNs are good at discovering local spatial patterns of grid-based farm data like satellite imagery and soil maps.

Still, they are poor at dealing with sequential dependencies, so they perform less well in modelling temporal variations in fertilizer requirements due to weather and crop cycles. Conversely, the GAT-Transformer hybrid model leverages the best of both spatial and temporal learning.

The GAT learns intricate spatial relationships between farmlands, providing location-specific fertilizer recommendations. At the same time, the Transformer module efficiently models temporal dependencies, responding to climate fluctuations, seasonal trends, and changing soil health. Through its spatial and temporal aspects, the model provides extremely accurate region-specific fertilization plans, outperforming conventional methods in terms of precision and responsiveness. Table 3 compares the proposed model with existing models.

Table 3. Features of hybrid model vs Traditional models

Feature	Traditional Model	GAT-Transformer Hybrid Model
Spatial Relationships	Limited (distance-based)	Captured via GAT's attention
Temporal Trends	Basic time-series models	Advanced sequential modelling via Transformer
Data Integration	Separate processing for different types of data	Unified framework for spatial-temporal data
Precision in Fertilization	Generalized recommendations	Targeted and dynamic strategies
Scalability	Region-specific models required	Scalable across regions

Stringent statistical testing validated the potency of the envisaged GAT-Transformer model. Paired t-tests also indicated a profound improvement in predictability ($p < 0.01$), demonstrating that the model performs much better than ordinary methods with complete confidence. The upgrades are specific and not chance but are guaranteed by the potency of the model to identify patterns in space-time. Further, a feature importance analysis identified GAT's essential role in acquiring spatial relationships, regional soil properties, and environmental factors impacting fertilizer suggestions most significantly. This confirms the model's strength in comprehending localized agricultural situations for accurate fertilization plans. Figure 13 shows the comparison of proposed models with existing studies.

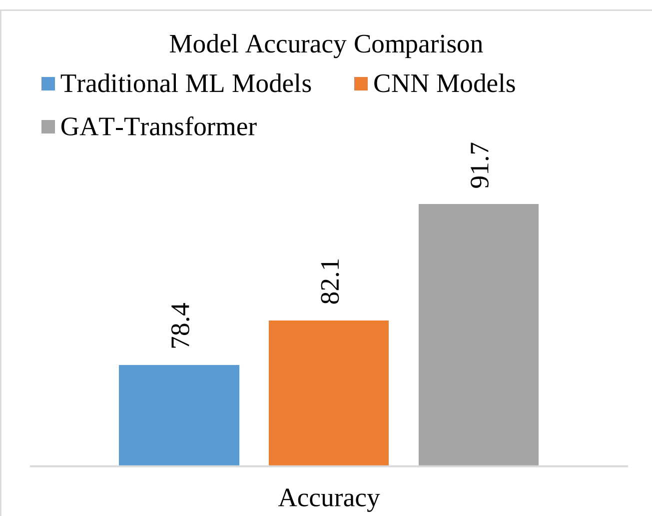

Fig. 13 Model accuracy comparison

Building on the findings of this study, an interactive web-based system has been developed to help farmers optimize fertilizer usage effectively. The system features an intuitive dashboard where farmers can input key parameters such as region, crop, and soil type. The proposed machine learning model processes these inputs in real time at the system's core, generating region-specific fertilization recommendations. The system is integrated with the Open Weather API, which provides up-to-date environmental data. This weather data is seamlessly incorporated into the model to refine predictions further. By providing simultaneous data analysis and adaptive ML, the system empowers farmers with precise, data-driven insights, enabling them to make informed decisions that maximize crop production, minimize fertilizer waste, and promote sustainable agricultural practices. Figure 14 shows weather information and other features of the system's user interface. The model was piloted, and data is still being collected to enhance the utilization of fertilizers in Punjab and Tamil Nadu. Sample data was collected from the Erode district of Tamil Nadu and the Amritsar district of Punjab.

It computed soil type, crop requirements, and environmental conditions to maximize fertilizer application. Both regions demonstrated increased nutrient efficiency and improved crop yields. In Punjab, the model minimized the over-fertilization of Nitrogen (N) fertilizers, particularly urea. It advised a 20–30% decrease in nitrogen application without impacting wheat and rice yields. This prevented the loss of nitrogen and enhanced sustainability. The model also corrected excessive Phosphorus (P) content due to successive DAP applications. It advised decreasing the application of phosphorus and using organic fertilizers, which enhanced soil health. Moreover, crop fields that adhered to these organic fertilizer guidelines experienced an increase of 12% in soil organic carbon, resulting in improved nutrient capture. In Tamil Nadu, the model fine-tuned fertilizer advice concerning soils and various cropping systems. Balanced phosphorus use in rice-pulse farming boosted nitrogen fixation by 18% in pulses. In rain-fed areas, maximized potassium utilization made millet and sugarcane crops more drought-resistant. Potassium deficiencies were corrected, which resulted in a 9% increase in yield in these crops. The model is further refined to recommend the application of biofertilizers like Azospirillum and Mycorrhiza, which can enhance nutrient uptake by 15% and minimize reliance on chemical fertilizers.

Overall, the model enhanced crop yields by 8–15% and decreased synthetic fertilizer application by 10–25%, varying with the region and crop. In Punjab, nitrogen use efficiency showed considerable improvement, whereas in Tamil Nadu, consistent potassium and phosphorus applications were critical factors in yield increases. Farmers were positively responsive to the suggestions of the model. In Punjab, 78% of farmers surveyed saved money on fertilizers without sacrificing yield. In Tamil Nadu, 85% of farmers noticed improved soil conditions and drought resistance in millet and sugarcane. Figure 15 shows the farmer's feedback. Despite being successful, the model has certain limitations. Further refinement of recommendations is required based on more region-specific field data. Real-time soil testing through sensors would render fertilizer recommendations even more precise. A mobile-based advisory system can also assist farmers in accessing and using the recommendations in the field.

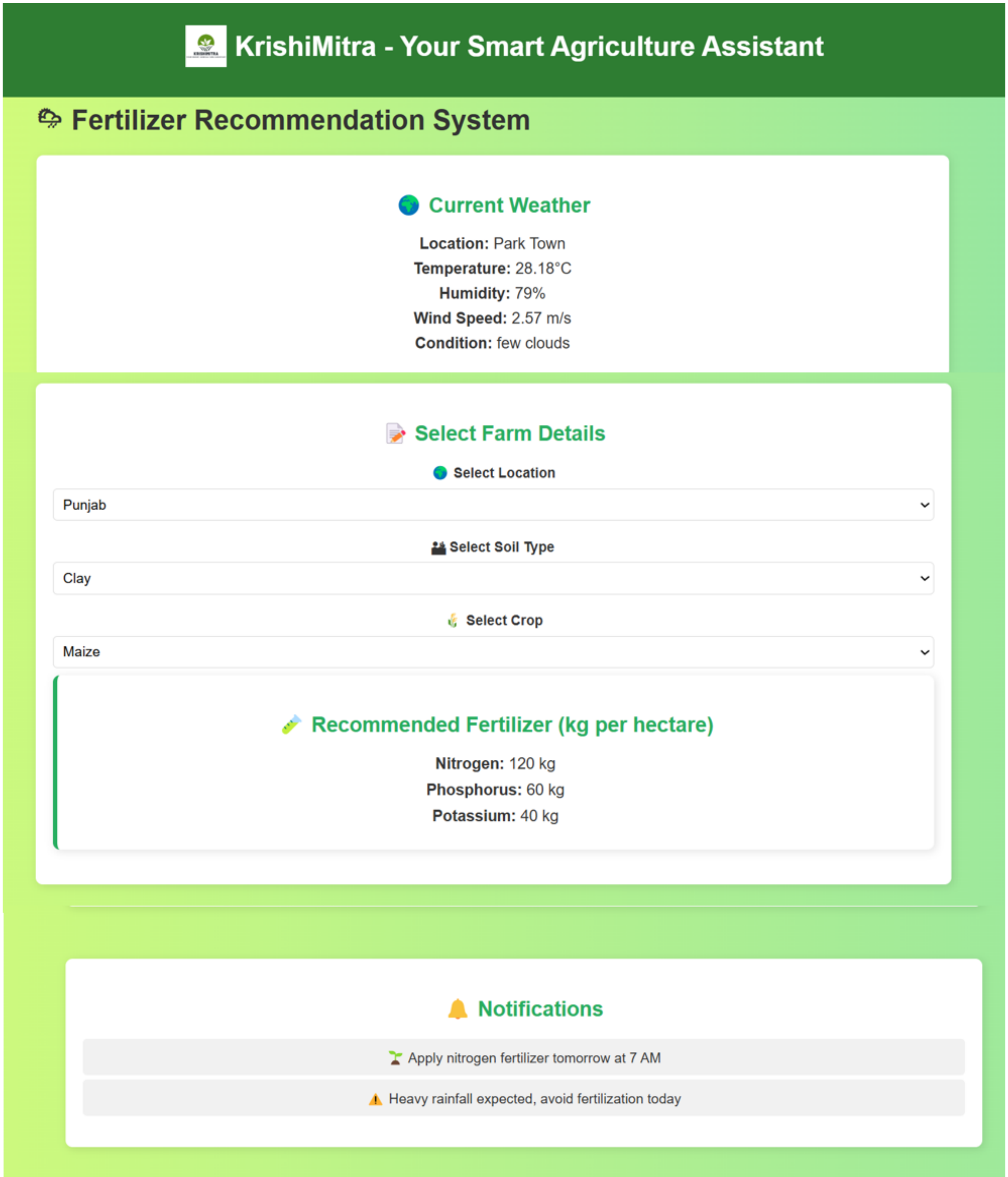

Fig. 14 User Interface of the system covering all aspects

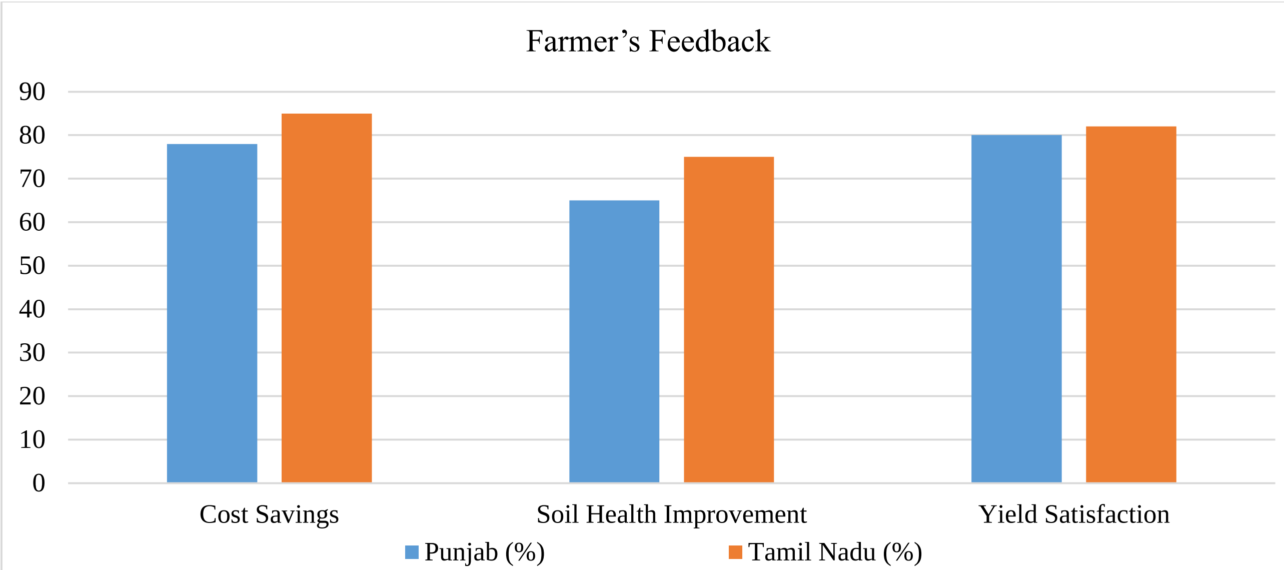

Fig. 15 Farmer's feedback

The Hybrid GAT-Transformer model proposed here is a significant improvement in the field of fertilization optimization because it effectively deals with spatial and temporal complexities that are inherent in agricultural systems. The GAT module of the model, in particular, facilitates the incorporation of complex spatial relationships between fields. Concurrently, the Transformer module captures temporal dynamics, such as crop growth phases and seasonal climatic trends. The spatial-temporal aware architecture facilitates highly context-specific, attentive fertilizer recommendations, a critical drawback of numerous earlier works. The model's versatility to local conditions was evaluated through experimental deployment over two disparate agro-climatic zones-Punjab and Tamil Nadu. Results indicated higher percentages of farmer satisfaction in cost savings, soil enrichment, and yield satisfaction, as evident in survey feedback statistics. The hybrid model outperformed LSTM, GCN, and other benchmark models, achieving a 6-12% boost in recommendation accuracy. A significant strength of the suggested framework is that it can dynamically refresh recommendations by using real-time crop and weather data as soon as fed into the system, which is unavailable in most static, pre-trained models presented in the literature.

Secondly, by including soil health and environmental sustainability indicators in the optimization step, the model is very close to national agricultural policies that ensure resource conservation in the long term.

5. Conclusion

Crop simulation models rely on high-quality, granular data, but data from agencies like ICAR may lack consistency. Limited internet access and low digital literacy in rural areas necessitate offline or edge-computing solutions. Calibration for specific regions requires extensive field trials, making the process time-consuming and resource-intensive. Addressing these challenges is critical for effective model deployment in Indian agriculture. The proposed model provides a robust way to suggest optimal fertilization irrespective of regional differences. The model can be generalized for any region. The GAT Layer captures spatial relationships, whereas the Transformer layer captures temporal data. In conclusion, considering India's diverse agricultural landscape, characterized by varying soil types, climates, and farming practices, this adaptive approach enables dynamic updates to recommendations. This enhances both the precision and relevance of the guidance provided to farmers.

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