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Soil Fertility Prediction Using Spatiotemporal Graph Neural Networks

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ABSTRACT

Soil health and fertility are essential components for effective farming. The maintenance of soil health is multipurpose. It supports both plant growth and tackles environmental issues like soil erosions. However, modern agricultural activities and the use of chemical fertilizers affect the quality of the soil. To improve the soil health, the timely prediction of soil fertility is needed. In this work, a deep learning model is proposed for accurate soil fertile prediction. The proposed model is based on a Spatiotemporal Graph Neural Network (STGNN) which considers both spatial and temporal properties of the soil for prediction. Further, the parameters of the model are modified using the metaheuristic optimization algorithm of Red Kite Optimizer. The model is trained and validated on a real-world soil dataset sourced from Kaggle, achieving a classification accuracy of 95.86%, an F1-score of 94.72%, and an RMSE of 0.089. Comparative analysis shows our STGNN model outperforms existing ML and DL models, including CNN, LSTM, and Random Forest, by 3.8% to 6.4% in prediction accuracy. This work provides a robust and scalable model for proactive soil management. It is used for data-driven decision-making in precision agriculture and contributes to long-term soil sustainability.

1. INTRODUCTION

Soil is a basic element of the ecosystem. The proper maintenance of soil health is needed to keep biodiversity and mitigate climate change [1]. Soil fertility plays a major role in ecosystems and agriculture. It directly influences crop yields and food security. Soil fertile helps the plants for their growth and balances the nutrients levels. Increasing soil health and fertility is important for a number of reasons, and it should be of the highest importance for all farmers. While the profits of healthy soil may not be instantly visible, the long-term effects of ignoring soil health can be devastating. In addition, soil health is majorly impacting both the atmosphere and the budget. The soil health reduction leads to decreased crop yields. This reduction can threaten food security and raise food prices for buyers.

Soil fertility refers to the soil's capability to supply basic nutrients to plants in adequate amounts and proportions for their growth and reproduction [2]. It involves a combination of physical, chemical, and biological properties, including nutrient content, pH level, soil texture, organic matter, and microbial activity. The components for soil fertility and their composition are given in Table 1.

There are different methods that farmers can apply to enhance soil health and fertility: Crop rotation, Cover cropping, Composting, Reduced tillage, Integrated pest management and Soil testing. Among these, soil testing is a key part of preserving soil health and fertility. By analyzing nutrient levels in the soil, farmers can identify the most effective fertilizers to enhance soil quality. Recently, Machine Learning (ML) and Deep learning algorithms have gained more attention in all fields. In the agriculture field, this algorithm is used for suitable crop recommendation, water quality prediction, soil quality prediction and rainfall prediction etc. [3, 4].

The ML and DL models are used for soil fertility prediction by analysing complex relationships between variables [5]. The steps involved in learning model-based soil analysis are given in Figure 1. ML models like decision trees, random forests, and support vector machines capture non-linear relationships but require complex feature extraction techniques. Conversely, DL models, particularly neural networks can extract the features automatically. In addition, the accuracy of the model is high with minimum training data. Based on predicted results, the action to improve soil health is carried out.

In this work, a new model is constructed for analysing the soil fertility. The model is based on integrating multiple learning layers to process the soil data effectively. The paper is organized into the following chapters. Chapter 2 presents a literature review of soil fertility prediction techniques. Chapter 3 describes the proposed model for prediction. Chapter 4 presents the experimental results; Chapter 5 presents the conclusions of the work.

Table 1. Components for soil fertile

Components	Composition
Macronutrients	Important elements like nitrogen (N), phosphorus (P), and potassium (K) are required in large quantities for plant growth.
Micronutrients	Elements such as zinc (Zn), copper (Cu), and manganese (Mn) are needed in smaller amounts but are crucial for plant health.
Soil pH	The acidity or alkalinity of the soil affects nutrient availability and microbial activity.
Organic Matter	Decomposed plant and animal residues that improve soil structure, water retention, and nutrient supply.
Soil Texture	The proportion of sand, silt, and clay particles, influencing water retention, drainage, and root penetration.
Microbial Activity	The presence of beneficial microorganisms that decompose organic matter, recycle nutrients, and enhance soil structure.

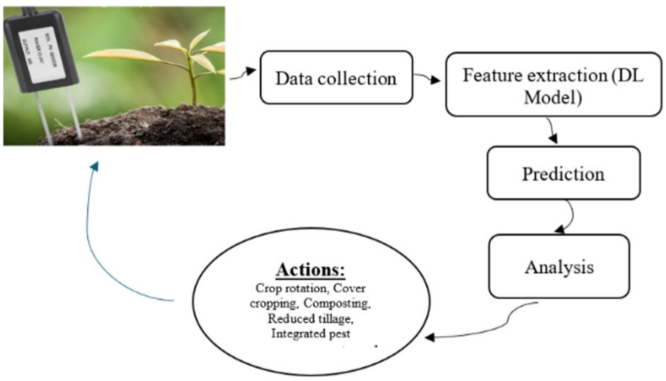

Figure 1. Soil analysis system

2. RELATED WORK

Recent advancements in soil fertility prediction have leveraged a wide array of machine learning, deep learning, and hybrid models. This section categorizes the existing literature based on methodological approaches and identifies key limitations to motivate the proposed work.

2.1 Machine learning-based models

Machine learning has been a foundational approach in soil fertility classification and crop recommendation. A notable contribution involves the use of the AdaBoost classifier for soil quality classification into low, medium, and good categories, with crop suggestions provided accordingly [6]. This model achieves improved accuracy when compared to other ML algorithms. Similarly, an ensemble model combining XGBoost, LightGBM, and CatBoost was introduced to capture complex data patterns. This model achieves a notable accuracy ranging between 3.6% and 8.2% over individual models [7]. The probability-based models have also found application in this domain. For instance, a Naive Bayes classifier was used to predict soil fertility by computing class probabilities and this approach proved efficient for larger datasets due to its low complexity [8]. Support Vector Machine (SVM) techniques have further been applied to fertilizer recommendation tasks by separating data into clusters via hyperplanes, enhancing classification precision [9].

2.2 Deep learning and neural network approaches

Deep learning techniques have emerged as powerful tools for modeling intricate soil nutrient dynamics. A DL-based model incorporating attention mechanisms was proposed to focus selectively on critical nutritional parameters. It achieves performance improvement of at least 9.5% compared to conventional approaches [10]. Further, CNN-based models have been applied to image data for soil fertility classification. It extracts textural features and achieves accuracy up to 93.23% after parameter tuning [11]. Some methods have combined feature extraction with sequential modeling. One such two-stage approach initially used Latent Dirichlet Allocation (LDA) to extract relevant features, followed by recurrent neural networks for time-series-based soil quality assessment [12]. An enhancement of this approach employed modified recurrent networks with novel activation functions to jointly model spatial and temporal soil patterns [13].

2.3 Hybrid and metaheuristic-optimized models

Hybrid models offer an alternative by combining different algorithms to leverage their respective strengths. For example, a model integrating Learning Vector Quantization and Probabilistic Neural Networks was developed to extract and fuse hidden features from soil data, achieving an average accuracy of 92.36% on test datasets [14]. Another approach used an artificial neural network optimized through a genetic algorithm to classify soil into "more" and "less" fertile categories, enhancing model adaptability [15]. A Gaussian Extreme Learning Machine (ELM) was also explored for soil fertility analysis, testing various activation functions and learning rates. The model yielded a prediction error of 14% and an overall accuracy of 91%, outperforming several classical ML models [16].

2.4 Sensor-enabled and IoT-based approaches

The integration of sensors and IoT technologies has facilitated the development of real-time soil monitoring systems. A wireless sensor-based platform was developed using NPK, pH, and air quality sensors. It is used for real-time nutrient assessment and crop recommendation [17]. In another system, Fuzzy C-Means (FCM) clustering was used to interpret soil data by calculating centroids and assigning membership functions to different data classes [18]. Feed-forward neural networks have also been applied to classify soil quality based on multiple micronutrient inputs, such as Zn, B, Cu, Fe, and Mn. Their performance was evaluated with different kernel and grid sizes to optimize classification [19]. A low-cost IoT-enabled system was proposed to recommend fertilizers by sending soil data to the cloud and processing it via fuzzy logic algorithms [20]. Unsupervised approaches like k-means clustering have been tested for classifying soil fertility [21]. To manage mixed-type soil attributes, a weighted C4.5 decision tree was proposed. It can effectively handling both categorical and continuous data [22].

Fuzzy inference systems have also been used to predict soil pH by incorporating inputs such as temperature, moisture, and organic matter. The model demonstrated low complexity and high accuracy on real-time datasets from Uttarakhand [23]. Deep learning approaches based on back-propagation neural networks have used local binary patterns to improve feature extraction [24]. A modified J48 decision tree algorithm has similarly been used for pH prediction, offering reduced complexity in handling sequential inputs [25].

Despite substantial advancements in soil fertility prediction, the existing literature presents several critical gaps. A prominent limitation is the lack of unified spatiotemporal modeling, where most models independently address either spatial or temporal variations in soil characteristics but not both in conjunction. To address these challenges, this study introduces a novel Spatiotemporal Graph Neural Network (STGNN) optimized using the Red Kite Optimizer (RKO). The proposed model effectively captures spatial relationships using Graph Convolutional Networks (GCN) and temporal dependencies through Gated Recurrent Units (GRU).

3. PROPOSED MODEL

In this work, a hybrid DL model is developed for soil fertility prediction. Initially, the soil parameters are collected. Then, the data are applied in a hybrid model for classification. The hybrid model includes both Graph Neural Networks (GNN) layers and temporal layers of Gated Recurrent Units (GRU) to learn both spatial and temporal features. Finally, the model is analyzed in terms of accuracy parameters. The architecture of the proposed model is given in Figure 2.

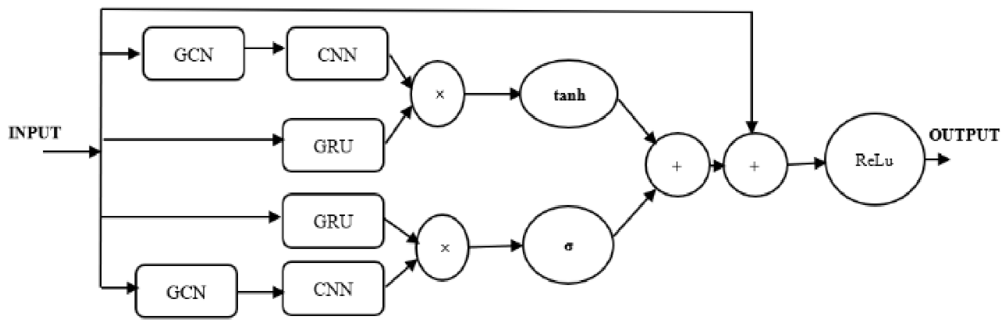

Figure 2. Model architecture

3.1 GNN

The GNN is used to model data that can be represented as graphs [26, 27]. In the graph, the nodes represent entities and the edges represent relationships between these entities. Graph Convolutional Networks (GCN) is also a type of GNN that operates directly on graph-structured data to capture spatial dependencies between nodes. For a node $v_i$with feature vector x, the updated feature vector after one GCN layer can be represented as Eq. (1):

$$x_i' = \sigma(\sum_{j \in N(i)} \frac{1}{\sqrt{|N(i)N(j)}} x_j \, W) \tag{1}$$

In the above equation, the $N(i)$ denotes the neighbors of node *i*. The W is the learnable weight matrix and σ is the activation function.

The operation of a GCN layer can be described by the following Eq. (2):

$$H^{(l+1)} = \sigma(D^{-1}AH^{(l)}W^{(l)}) \tag{2}$$

In the above equation, the $H^{(l+1)}$ input feature matrix at layer l. A is the adjacency matrix and D is the degree matrix of A. $W^{(l)}$ is the learnable weight matrix at layer l.

3.2 GRU

GRUs can capture temporal dependencies in sequential data by maintaining a hidden state that evolves over time [28]. The operations of GRU mainly depend on reset gate (r_t) and update gate (z_t). The reset gate controls the amount of past data that should be deleted. The update gate determines the amount of data that should be forwarded to the next stage. The h_t and h'_t are the hidden and candidate hidden states. The operation of a GRU layer can be described by the following Eqs. (3) to (6):

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{3}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{4}$$

$$h'_t = tanh(W_h x_t + r_t \odot U_h h_{t-1} + b_h) \tag{5}$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'_t \tag{6}$$

In the above equation, the x_t is the input at time step *t*. $W_h, W_z, W_r, U_h, U_r, U_h$ are learnable weights. The b_z, b_r and b_h are bias terms.

3.3 Red kite optimization (ROA) algorithm

Metaheuristics algorithms are used to solve real-world issues [29]. ROA is inspired by the behavior of red kites for their survival. It is proposed by Alshareef and Fathy [30] to solve the problem of electric consumption prediction.

Normally, red kites build their nests near lakes for easier hunting. The group of red kites lives together. It has unique attitudes like high speed when hunting, and also the special sounding behavior to alert others in case of enemies' attacks, storms, and identifying food. This behavior is mathematically modelled to find an optimal solution in the search space. It has three stages: initialization, choosing the team head and moving to another location.

3.4 Initialization phase

The population of red kites is generated randomly in this phase. It can be expressed as follows Eq. (7):

$$P_{i,j}(t) = ll + r \times (ul - ll) \quad (7)$$

In the above equation, $P_{i,j}(t)$ is the position of red kites as s function of iteration *t*. ll and ul is the lower limit and upper limit of the search space. *r* is the random number.

3.5 Choosing the team head

Among the group, the team head is identified to lead the team further. It can be modelled as follows Eq. (8):

$$\overrightarrow{best(t)} = \overrightarrow{P_{i,j}(t)} \text{ if } f_i(t) < f_{best}(t) \quad (8)$$

In the above equation, $\overrightarrow{best(t)}$ is the best location for red kite. $f_i(t)$ is the fitness function of the optimization. $f_{best}(t)$ is the fitness function for the team head.

3.6 Movement of red kite

To balance the exploration and exploitation stages, the birds are moved from one location to a new location. The varying coefficient is expressed as follows (Eq. (9)):

$$D = (\exp\left(\frac{t}{t_{max}}\right) - \frac{t}{t_{max}})^{-10} \quad (9)$$

The new location of the bird is expressed as follows Eq. (10):

$$\overrightarrow{p_i^{new}(t+1)} = \overrightarrow{p_i(t)} + \overrightarrow{p_{mi}(t+1)} \quad (10)$$

In the above equation, $p_i^{new}(t+1)$ is the new position of the bird updated as follows Eq. (11) to Eq. (14).

$$\overrightarrow{p_{mi}(t+1)} = \mathrm{D}(t) \times \overrightarrow{p_{mi}(t)} + \overrightarrow{e1(t)} \odot (\overrightarrow{p_{rws}(t+1)} - \overrightarrow{p_i(t)}) + \overrightarrow{e2(t)} \odot (\overrightarrow{best(t)} - \overrightarrow{p_i(t)}) \quad (11)$$

where, $p_{rws}(t+1)$ is a red kite position based on a roulette wheel. e1 and e2 are the random vectors.

$$\overrightarrow{p_i^{new}(t+1)} = \max(\min\left(\overrightarrow{p_i^{new}(t+1)} + ul\right), ll) \quad (12)$$

$$\begin{cases} \overrightarrow{e1(t+1)} = \overrightarrow{r_1} \\ e2(t+1) = \overrightarrow{r_2} \end{cases} \text{if rand<=0.5} \quad (13)$$

$$\begin{cases} \overrightarrow{e1(t+1)} = \overrightarrow{r_3} \\ e2(t+1) = \overrightarrow{r_1} \end{cases} \text{otherwise} \quad (14)$$

where, $\overrightarrow{r_1}$, $\overrightarrow{r_2}$ and $\overrightarrow{r_3}$ are random vectors vary from zero to three.

The parameter tuning in the proposed hybrid DL model for soil fertility prediction is crucial for enhancing model performance. By carefully adjusting the parameters, the model can effectively capture the complex spatial and temporal dependencies in soil data for more accurate predictions. The Pseudocode for proposed parameter tuning is given below:

```
# Pseudocode for Red Kite Optimization Algorithm (ROA)
# Initialize parameters
population_size=N
max_iterations=T
lower_limit=ll
upper_limit=ul
# Function to initialize the population
def initialize_population(N, ll, ul):
return [ll+(ul-ll)*random.random() for_in range(N)]
# Function to evaluate the fitness of the population
def evaluate_fitness(population):
return [fitness_function(individual) for individual in population]
# Function to identify the best solution in the population
def identify_best_solution(population, fitness):
best_index=fitness.index(min(fitness))
return population[best_index]
# Function to select a red kite using the roulette wheel method
def roulette_wheel_selection(population, fitness):
max_fitness=max(fitness)
selection_probs=[max_fitness-f for f in fitness]
total_prob=sum(selection_probs)
selection_probs=[p/total_prob for p in selection_probs]
return population[np.random.choice(len(population), p=selection_probs)]
# Function to generate a random vector
def random_vector():
return random.random()
Initialize the population
population=initialize_population(population_size, lower_limit, upper_limit)
# Evaluate the fitness of the initial population
fitness=evaluate_fitness(population)
# Identify the best solution in the initial population
best_solution=identify_best_solution(population, fitness)
# Main loop
for t in range(max_iterations):
  for i in range(population_size):
    # Update the position of each red kite
    D=((exp(t / max_iterations) - t / max_iterations) / 10) ** (-1)
    p_mi=(D*population[i]+
random_vector()*(roulette_wheel_selection(population, fitness) - population[i])+
        random_vector()*(best_solution-population[i]))
        new_position=population[i]+p_mi
        # Ensure the new position is within bounds
    new_position=max(min(new_position, upper_limit), lower_limit)
       # Update the population
    population[i]=new_position
    # Evaluate the fitness of the updated population
  fitness=evaluate_fitness(population)
    # Update the best solution
  best_solution=identify_best_solution(population, fitness)
# Output the best solution
return best_solution
```

In this pseudocode, initialize_population generates the initial population of red kites. evaluate_fitness evaluates the fitness of each red kite in the population. identify_best_solution identifies the best solution in the population. random_vector1 and random_vector2 generate random vectors. roulette_wheel_selection selects a red kite based on the roulette wheel method. Finally, the best solution is returned after the main loop is completed.

Unlike Particle Swarm Optimization (PSO) [31] and Genetic Algorithm (GA) [32], ROA adapts dynamically to complex search spaces. This adaptation is used for efficient convergence without getting trapped in local optima. PSO is based on velocity updates influenced by global and local optima and may get trapped in local minima in rugged landscapes. GA involve crossover and mutation and may require more generations to converge.

4. RESULT AND DISCUSSION

The soil data is collected from the Kaggle website (https://www.kaggle.com/datasets/rahuljaiswalonkaggle/soil-fertility-dataset). The data set includes different soil nutrition parameters. The visualization of a data set is given in Figure 3.

The proposed model is coded in Python IDLE 3.7.0. The library files of TensorFlow and scikit-learn are used for analyzing the data. From the data set, 80% of the data is used to train the hybrid model and the remaining 20% data is used for validation purposes. The histogram of each variable is given in Figure 4.

The total sample count in the data set is 3773. A total of 697 and 58 non-fertile and fertile cases are tested on the trained model.

The training and validation accuracy of proposed a model over 100 epochs is given in Figure 5. There is a sharp increase in both training and validation accuracy that indicates the model learns quickly. Both training and validation accuracies are high which shows that the model is performing well overall.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	N	P	K	pH	EC	OC	S	Zn	Fe	Cu	Mn	B	Output
2	138	8.6	560	7.46	0.62	0.7	5.9	0.24	0.31	0.77	8.71	0.11	0
3	213	7.5	338	7.62	0.75	1.06	25.4	0.3	0.86	1.54	2.89	2.29	0
4	163	9.6	718	7.59	0.51	1.11	14.3	0.3	0.86	1.57	2.7	2.03	0
5	157	6.8	475	7.64	0.58	0.94	26	0.34	0.54	1.53	2.65	1.82	0
6	270	9.9	444	7.63	0.4	0.86	11.8	0.25	0.76	1.69	2.43	2.26	1
7	220	8.6	444	7.43	0.65	0.72	11.7	0.37	0.66	0.9	2.19	1.82	0
8	220	7.2	222	7.62	0.43	0.81	7.4	0.34	0.69	1.05	2	1.88	0
9	207	7	401	7.63	0.59	0.69	7.6	0.32	0.68	0.62	2.43	1.68	0

Figure 3. Dataset visualization

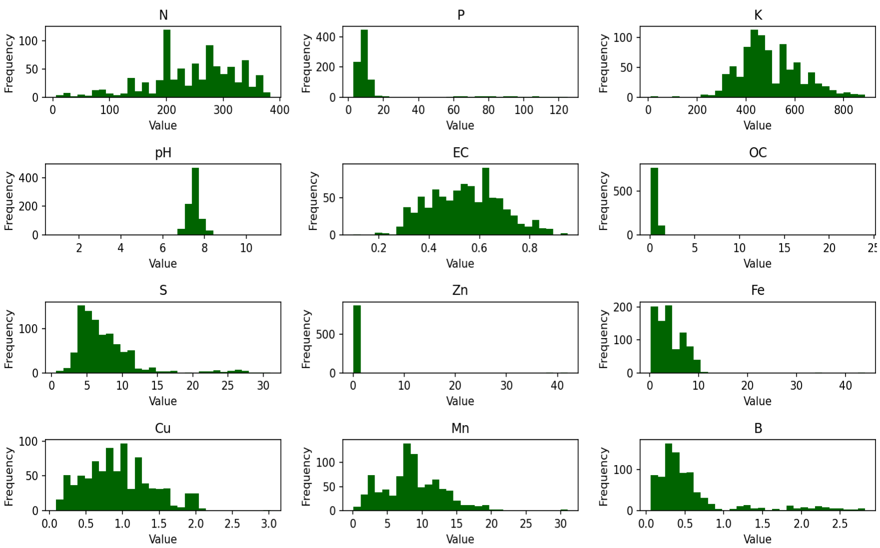

Figure 4. Plot of attributes

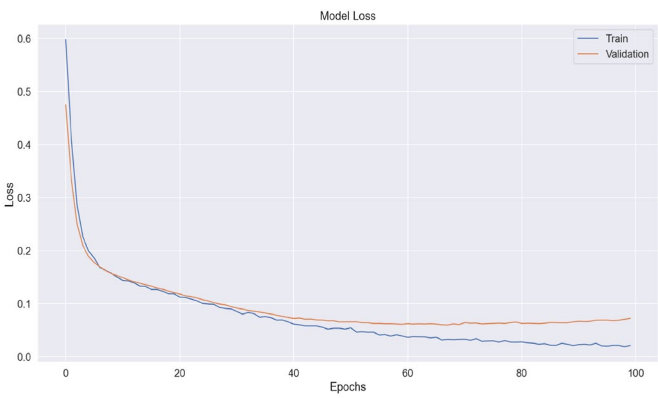

Figure 5. Loss analysis of the model

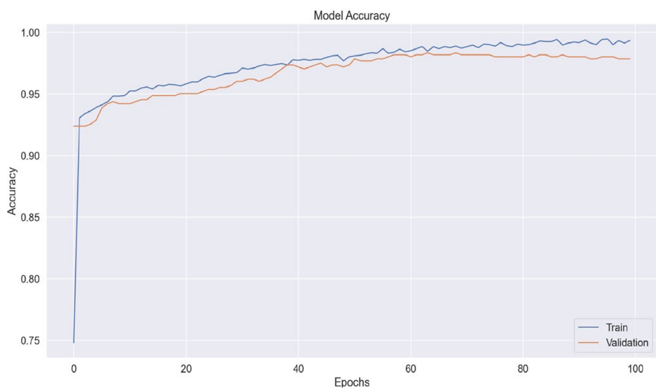

Figure 6. Accuracy analysis of the model

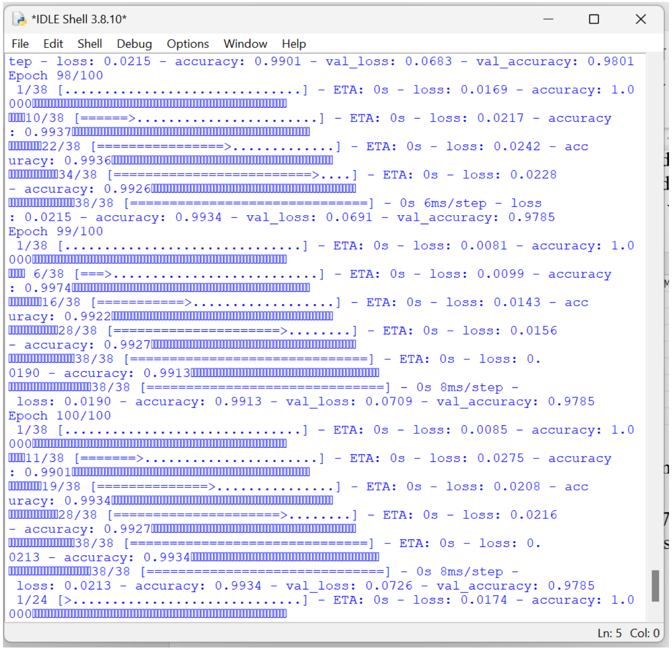

Figure 7. Model training

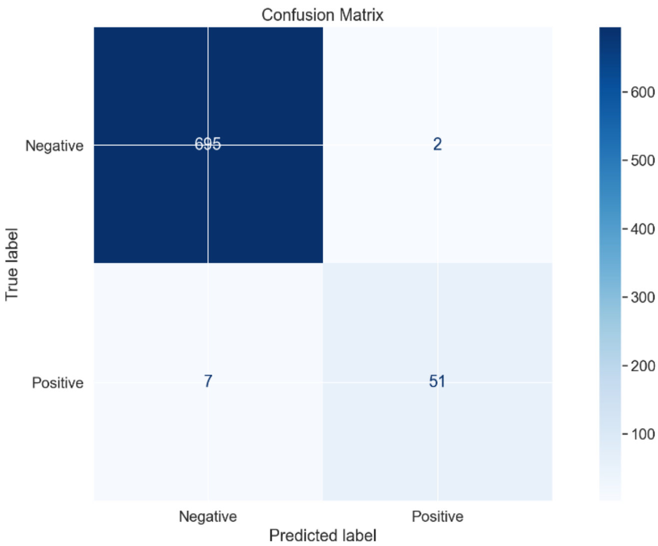

Figure 8. Confusion matrix plot

The training and validation loss of proposed a model over 100 epochs is given in Figure 6. The training and validation losses are very close to each other which indicates that the model is learning in a balanced manner. The model training accuracy as a function of an epoch is given in Figure 7.

Figure 8 shows the confusion matrix for the classification. The model correctly predicted the negative class 695 times and the positive class 50 times. It incorrectly predicted the positive class 2 times and the negative class 8 times.

The proposed model is analyzed in terms of Accuracy, Precision, Recall and F1Score rates. The overall performance of the model is given in Table 2. The hybrid model achieved better performance than other models with the highest accuracy, Precision**,** Recall and F1 Score rates. The model attained an accuracy of 98.75%, with a Precision score of 96.15%, and a Recall score of 86.21%. The next best model is CNN+Bi-GRU, with a 95.50% accuracy, a 92% Precision score, and an 80% Recall score. The poorest model performance model was the CNN, with an accuracy of 86.50%, a Precision score of 80%, and a Recall score of 60. To validate the superiority of the proposed model, statistical significance testing are conducted. We used the paired t-test and computed the p-values between the proposed model and each baseline model for performance metrics, primarily focusing on accuracy. The hypothesis is defined as a null hypothesis (H_0) and an Alternative hypothesis (H_1). In Null hypothesis, there is no significant difference between the proposed model and the baseline models. In the Alternative hypothesis (H_1), the proposed model significantly outperforms the baseline models. A significance level of $\alpha=0.05$ was chosen. If $p<0.05$, the null hypothesis is rejected. The performance of the model is graphically shown in Figure 9.

Table 2. Performance analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	P-Value (Vs. Proposed Model)
Proposed model	98.68	96.15	86.21	90.71	--
CNN+Bi-GRU	95.50	92.00	80.00	85.50	0.0007
CNN+GRU	93.25	89.50	75.00	81.25	0.0012
CNN+LSTM	91.00	87.00	70.00	77.50	0.0016
LSTM	88.75	84.50	65.00	73.50	0.0028
CNN	86.50	82.00	60.00	70.00	0.0032

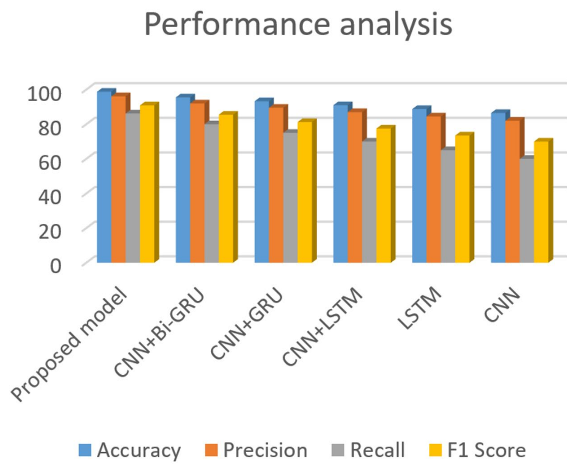

Figure 9. Overall performance analysis

Table 3. Performance comparison on SSURGO dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE
Random Forest	84.2	82.9	83.5	83.2	0.176
SVM	82.5	80.7	81.2	81.0	0.189
LSTM	86.1	85.4	84.9	85.1	0.163
GCN	87.5	86.8	87.1	86.9	0.151
Proposed ST-GNN+RKO	91.3	90.7	90.2	90.4	0.122

To address the limitation of the Kaggle dataset—specifically the lack of detailed geographic coverage and temporal resolution—we extended our experimental evaluation using the Soil Survey Geographic Database (SSURGO)[https://agdatacommons.nal.usda.gov/articles/dataset/Soil_Survey_Geographic_Database_SSURGO_/24660303]. SSURGO offers detailed soil property data across diverse

U.S. regions with fine-grained spatial resolution. The measured results are given in Table 3. The results on the SSURGO dataset confirm the robustness and generalization capability of our model across datasets with higher spatial granularity.

5. CONCLUSION

In this work, a new DL-based prediction model is proposed for soil fertility. The early prediction of soil fertile status supports the farmers in maintaining soil health and increases agriculture yields. Here, the hybrid model combines both graph neural networks and gated recurrent units for accurate prediction. Moreover, the model parameters are tuned using a red kite optimizer. Results on data sets show that the hybrid model has better performance than other models, where the overall accuracy value is 98.75%, The overall precision value is 96.15%, the overall recall value is 86.21% and the overall f1-score is 90.91%. Beyond the immediate improvements in prediction accuracy, this work opens avenues for precision agriculture systems that are responsive to dynamic environmental changes. The ability to generalize this approach to other domains—such as crop yield forecasting, climate impact analysis, and smart irrigation planning—positions it as a foundational step toward intelligent agricultural ecosystems. Future research will explore the deployment of the proposed model in real-time sensor networks and its extension to multi-modal data sources.

REFERENCES

[1] Gowdy, J. (2020). Our hunter-gatherer future: Climate change, agriculture and uncivilization. Futures, 115: 102488. https://doi.org/10.1016/j.futures.2019.102488

[2] Hartemink, A.E. (2006). Assessing soil fertility decline in the tropics using soil chemical data. Advances in Agronomy, 89: 179-225. https://doi.org/10.1016/S0065-2113(05)89004-2

[3] Food and Agriculture Organization of the United Nations. (2020). Global Soil Partnership. https://www.fao.org/global-soil-partnership/areas-of-work/soil-fertility/en.

[4] Wang, F., Harindintwali, J.D., Yuan, Z., Wang, M., et al. (2021). Technologies and perspectives for achieving carbon neutrality. The Innovation, 2(4): 100180. https://doi.org/10.1016/j.xinn.2021.100180

[5] Sakthivel, B., Jayaram, K., Devarajan, N.M., Basha, S.M., Rajapriya, S. (2022). Machine learning-Based pruning technique for low power approximate computing. Computer Systems Science & Engineering, 42(1). http://doi.org/10.32604/csse.2022.021637

[6] Reddy, T.V., Saikumar, K., Reddy, R.A., Chary, V.B., Srinija, P., Reddy, T.H.V. (2024). Integrating soil sensing and rainfall modelling for precision crop recommendation systems. In 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), Pune, India, pp. 1-6. https://doi.org/10.1109/I2CT61223.2024.10543793

[7] Sunori, S.K., Negi, P.B., Joshi, N.C., Mittal, A., Juneja, P. (2024). Soil fertility assessment using ensemble methods in machine learning. In 2024 5th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV). Tirunelveli, India, pp. 17-21. https://doi.org/10.1109/ICICV62344.2024.00010

[8] Agarwal, S., Bhangale, N., Dhanure, K., Gavhane, S., Chakkarwar, V.A., Nagori, M.B. (2018). Application of colorimetry to determine soil fertility through naive bayes classification algorithm. In 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Bengaluru, India, pp. 1-6. https://doi.org/10.1109/ICCCNT.2018.8494113

[9] Khan, A.A., Faheem, M., Bashir, R.N., Wechtaisong, C., Abbas, M.Z. (2022). Internet of Things (IoT) assisted context aware fertilizer recommendation. IEEE Access, 10: 129505-129519. https://doi.org/10.1109/ACCESS.2022.3228160

[10] Kumar, A., Kanthi, S., Vinaykumar, M.R., Hemanth, M., Hemanth, P. (2023). A systematic exploration of sensor-based approaches for soil nutrient monitoring and optimization. In 2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkur, India, pp. 1-6. https://doi.org/10.1109/ICMNWC60182.2023.10435724

[11] Natsir, M.S., Palantei, E., Nurtanio, I., Suyuti, A. (2023). Classification of soil fertility level based on texture with convolutional neural network (CNN) algorithm. In 2023 5th International Conference on Cybernetics and Intelligent System (ICORIS), Pangkalpinang, Indonesia, pp. 1-6. https://doi.org/10.1109/ICORIS60118.2023.10352265

[12] Kathiravan, M.N., Bande, S., Tiwari, S., Koshariya, A.K., Suganthi, D. (2023). Soil analysis and classification to improve the crop yield in agriculture using fast graph-CRNN approach. In 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), Erode, India, pp. 98-104. https://doi.org/10.1109/ICSSAS57918.2023.10331819

[13] Bu, Y., Yu, X., Yang, Y. (2023). Soil nutrient evaluation system based on improved recurrent neural network. In 2023 3rd International Conference on Neural Networks, Information and Communication Engineering (NNICE), Guangzhou, China, pp. 149-153. https://doi.org/10.1109/NNICE58320.2023.10105705

[14] Sunori, S.K., Mohan, L., Pant, M., Juneja, P. (2023). Classification of soil fertility using LVQ and PNN techniques. In 2023 8th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, pp. 1441-1446. https://doi.org/10.1109/ICCES57224.2023.10192793

[15] Sunori, S.K., Negi, P.B., Garia, P., Arora, S., Lohani, M.C., Mittal, A., Juneja, P. (2022). Design of ANN based classifiers for soil fertility of Uttarakhand. In 2022 3rd International Conference for Emerging Technology (INCET). Belgaum, India, pp. 1-5. https://doi.org/10.1109/INCET54531.2022.9825273

[16] Prabavathi, R., Chelliah, B.J. (2022). An optimized Gaussian Extreme Learning Machine (GELM) for predicting the crop yield using soil factors. In 2022 International Conference on Electronic Systems and Intelligent Computing (ICESIC), Chennai, India, pp. 219-222. https://doi.org/10.1109/ICESIC53714.2022.9783578

[17] Rekha, B.N., Banuprakash, G.C. (2023). An approach to Analyzing the importance of air quality, soil humidity

and PH level using WSNs in the agriculture sector. In 2023 IEEE Fifth International Conference on Advances in Electronics, Computers and Communications (ICAECC), Bengaluru, India, pp. 1-6. https://doi.org/10.1109/ICAECC59324.2023.10560143
[18] Sunori, S.K., Mittal, A., Singh, N., Manu, M., Juneja, P. (2023). Fuzzy c-means clustering of soil data samples. In 2023 3rd International Conference on Intelligent Technologies (CONIT), Hubli, India, pp. 1-4. https://doi.org/10.1109/CONIT59222.2023.10205937
[19] Sujatha, M., Jaidhar, C.D. (2023). CNN-based soil fertility classification with fertilizer prescription. In 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, pp. 439-444. https://doi.org/10.1109/ICSCCC58608.2023.10176841
[20] Senthil, S., Remya, P. (2023). Design and implementation of biosensors for soil fertility prediction and management using IoT. In 2023 Eighth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), Chennai, India, pp. 1-6. https://doi.org/10.1109/ICONSTEM56934.2023.10142326
[21] Sunori, S.K., Pant, J., Pant, H., Manu, M., Juneja, P. (2022). Design of K-means clustering & SVM based models for soil fertility classification. In 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, pp. 862-866. https://doi.org/10.1109/ICOSEC54921.2022.9951872
[22] Feng, Y., Yang, J. (2022). Application of game analysis and mathematical optimization model in soil fertility evaluation intelligent monitoring system. In 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, pp. 123-126. https://doi.org/10.1109/ICAAIC53929.2022.9793192
[23] Sunori, S.K., Pant, J., Maurya, S., Mittal, A., Arora, S., Juneja, P., Nainwal, D. (2021). Neuro-fuzzy based prediction of pH value of soil of Uttarakhand. In 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, pp. 245-252. https://doi.org/10.1109/ICOEI51242.2021.9452814
[24] Sumiharto, R., Hardiyanto, R. (2018). NPK soil nutrient measurement prototype based on local binary pattern and back-propagation. In 2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS), Bali, Indonesia, pp. 23-28. https://doi.org/10.1109/IOTAIS.2018.8600858
[25] Pawar, M., Chillarge, G. (2018). Soil toxicity prediction and recommendation system using data mining in precision agriculture. In 2018 3rd International Conference for Convergence in Technology (I2CT), Pune, India, pp. 1-5. https://doi.org/10.1109/I2CT.2018.8529754
[26] Du, L., Tang, Y., Yuan, Y. (2022). A link prediction method based on graph neural network using node importance. In International Conference on Knowledge Science, Engineering and Management. Cham: Springer International Publishing. Springer, Cham, pp. 337-348. https://doi.org/10.1007/978-3-031-10986-7_27
[27] Gao, M., Li, Y., Yu, J. (2021). Workload prediction of cloud workflow based on graph neural network. In International Conference on Web Information Systems and Applications. Cham: Springer International Publishing. Springer, Cham, pp. 169-189. https://doi.org/10.1007/978-3-030-87571-8_15
[28] Wu, J., Tang, X., Zhou, D., Deng, W., Cai, Q. (2024). Application of improved DBN and GRU based on intelligent optimization algorithm in power load identification and prediction. Energy Informatics, 7(1): 36. https://doi.org/10.1186/s42162-024-00340-4
[29] Ganesamoorthy, N., Sakthivel, B., Balasubadra, K. (2024). Hen maternal care inspired optimization framework for attack detection in wireless smart grid network. International Journal of Informatics and Communication Technology, 13: 123-130.
[30] Alshareef, S.M., Fathy, A. (2023). Efficient red kite optimization algorithm for integrating the renewable sources and electric vehicle fast charging stations in radial distribution networks. Mathematics, 11(15): 3305. https://doi.org/10.3390/math11153305
[31] Kennedy, J., Eberhart, R. (1995). Proceedings of ICNN'95-international conference on neural networks. Particle Swarm Optimization, Perth, WA, Australia, 4: 1942-1948. https://doi.org/10.1109/ICNN.1995.488968
[32] Alhijawi, B., Awajan, A. (2024). Genetic algorithms: Theory, genetic operators, solutions, and applications. Evolutionary Intelligence, 17(3): 1245-1256. https://doi.org/10.1007/s12065-023-00822-6