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Hybrid AI Model for Soil Fertility Prediction and Fertilizer Optimization

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Abstract: Excessive use of pesticides and fertilizers in agriculture has led to issues such as soil erosion, water pollution, low microbial activity, and rising production costs [3]. This is crucial for sustainable agriculture, as it determines crop growth, nutrient balance, and environmental protection. However, standard methods of soil testing include laboratory tests; hence, they are time-consuming, costly, and not readily available to farmers. Such issues can cause delays in decision making, which leads to inefficient fertilizer use and long-term soil degradation. To address these issues, an AI-based Soil Fertility Prediction System was designed. The system uses data from Soil Health Cards (SHC), current weather data, and leaf colour chart (LCC) analysis to make timely and accurate recommendations. The system uses LSTM, a deep learning algorithm, to predict soil parameters, such as pH, nitrogen, phosphorus, and potassium, and weather parameters [8] such as temperature, humidity, rainfall, and wind speed. EfficientNetB0, a light deep-learning model, considers leaf images captured by farmers to detect nitrogen deficiency using LCC-based classification. [2] Both models are merged using a weighted average method, which gives a Soil Fertility Score (SFS) representing soil health and optimal fertilizer requirement. According to this score, farmers provide detailed instructions on how many nutrients are to be utilized. This prevents the overuse of chemicals and allows crops to grow well. The system is web deployable, thus providing easy access to farming communities. With computer vision and deep learning, this method allows for better decisions, minimizes soil damage, and allows sustainable farming.

Keywords: Soil Fertility Prediction, Fertilizer Optimization, Hybrid AI Model, Deep Learning in Agriculture, Soil Nutrient Analysis, Nutrient Deficiency Detection 20]

1.0 INTRODUCTION

Recent farming practices involve the excessive application of fertilizers and pesticides, which has led to low-quality soil, reduced productivity, and soil pollution for farmers. The amount and type of fertilizer used is usually a matter of guesswork or one of postponing laboratory analysis, which can lead to wasteful use of nutrients and soil degradation over the long term. Conventional soil analysis techniques involve laboratory testing of chemical attributes, such as pH, nitrogen (N), phosphorus (P), and potassium (K). While precise, these processes take time and money, and are not within the reach of every farming community, [22] particularly small farmers in rural areas. Consequently, decision-making takes a hit for the sake of timeliness, affecting crop productivity and soil viability. To address these challenges, artificial intelligence (AI) and deep learning have been proposed as saviour solutions [15]. In this study, we present a hybrid artificial intelligence (AI) model for soil fertility prediction and fertilizer optimization. The model is inspired by two robust methods: EfficientNetB0, which is used to scan leaf colour images to determine nutrient deficiencies according to the leaf colour chart (LCC) criteria, and Long Short-Term Memory (LSTM) networks, which are used to scan time-series data on Soil Health Cards (SHC) and prevailing weather conditions. This hybrid approach ensures an accurate, scalable, and inexpensive solution for precision agriculture, particularly for smallholder farmers. Classic agricultural prediction models tend to be based on past weather patterns and fixed soil conditions. These methods fail to keep pace with the changing, highly variable nature of climate change [24], and thus fail to provide a good fit when used in real-time predictions of soil fertility or fertilizer application optimization. To meet these challenges, current research is trending towards the use of deep learning-based methods, which are better suited to picking up both spatial and temporal patterns within complex agricultural datasets. This hybrid architecture, referred to in our project as LLC Net (Leaf and Land Condition Network), fuses both spatial and temporal information to calculate a fertility score [9], which guides fertilizer recommendations. By merging an Efficient Net and LSTM, the model ensures both visual and data-driven validation of soil conditions, thereby improving the accuracy, flexibility, and scalability of traditional systems.

1.1 RELATED WORKS

The purpose of the literature review of crop yield forecasting is to understand and synthesize a vast amount of information in this field, which falls under the field of agricultural research. This broad overview of historical research, methodology, and results in agricultural yield forecasting research aims to fulfil a number of primary functions. First, through the aggregation of current knowledge in the field of agricultural yield forecasting, the literature review sets the background from which to move forward. Subsequently, it places into context the various variables and conditions surrounding crop yields, emphasizing the characteristics of the agricultural climate. Contextualization is important so that researchers and readers can better appreciate the conditions under which new forecast models are being formulated and calibrated. In addition, the literature review plays a significant role in putting into perspective gaps, weaknesses, and issues in current research. By critically assessing previous findings and methodologies, researchers can establish where there is a potential for enhancement. This makes agricultural science, in general, more robust, but also aids in enhancing predictive models. This work employed LSTM time-series analysis and mentioned the use of deep learning models. The LSTM algorithm surpassed the RNN method in terms of accuracy, achieving an accuracy of 93%. Srinivas [8] suggested a project to estimate agricultural output based on factors such as field area, soil moisture content, temperature, and humidity.

The Random Forest algorithm was effective for predicting crop productivity. Recommending the appropriate fertilizer ratio can enhance crop productivity.[10] The machine learning method is used for agricultural yield prediction, assisting farmers in selecting the correct crops and applying the correct amount of fertilizer. B.G. Chaitra, B.M. Sagar, N.K. Cauvery. Padmashree [3] focused on the significance of deep learning in forecasting crop productivity and evaluating its performance using different machine learning methods. It also addresses the application of three algorithms: (DNN), Random Forest (RF), and XGBoost (extreme gradient boosting). Among them is the Deep Neural Network, to accurately predict crop yield Deep Neural Network (DNN) achieved the highest crop yield prediction accuracy, 96%. Random Forest (RF) accuracy: 92.9%- 93.3% accuracy rate for Extreme Gradient Boosting (XGBoost) and 96% accuracy for Deep Neural Networks (DNNs). Pardeep Kaur, Preeti Singh, Charu Madhu, Nidhi Garg, the current study discusses the prediction of wheat yield based on a CNN-LSTM model. Deep learning model CNN-LSTM for predicting wheat yield CNN-LSTM model is better than existing deep learning Predictive models based on deep learning are suitable.[6] Zheng Li, Ruosi Xu, Xiaoru Luo, Xin Cao Used an improved CNN structure and BiLSTM network, The proposed hybrid model boosts the precision of wind power prediction.[9] The hybrid model proposed in this study is better in terms of predictions. Deep learning, signal decomposition, and data processing were integrated into the wind-power prediction model. Malika Kulyal, Parul Saxena, provides for the use of CNN and the DNN, both Deep Learning algorithms, Crop prediction of yield involves supervised machine learning techniques such as Random Forest. Deep learning techniques, such as CNN and DNN, have also been applied. A machine learning algorithm was utilized to forecast crop yields. Typically, deep learning methods and random forests are employed. Research is conducted on machine learning techniques to predict crop productivity.[13] Preeti Saini, Bharti Nagpal, Puneet Garg, Sachin S.Kumar, suggested a hybrid CNN-Bi-LSTM deep learning-based method for sugarcane yield forecasting based on ARIMA Traditional Stacked-LSTM, Holt-winter Time-series, and GPR methods are blended with a hybrid CNN-Bi-LSTM_CYP deep learning approach.[8] The CNN-BILSTM_CYP approach was superior to traditional methods Dilli Paudel, Allard de Wit, Hendrik Boogaard, Diego Marcos, Sjoukje A. Osinga, Ioannis N. Athanasiadis, In Germany, compared LSTM and 1DCNN models with soft wheat LSTM and 1DCNN models are compared based on their performance and interpreting ability in forecasting agricultural production.[8] S.S. Olofintuyi, E.A. Olajubu, DejiOlanike, in this research, a deep learning approach to forecasting cocoa yield based on a CNN and RNN with LSTM (long short-term memory) is presented.[7]

Forecasting the cocoa yield using a deep learning approach (CNN-RNN + LSTM) is efficient. The minimum mean absolute error was achieved by using the proposed CNN-RNN with the LSTM model. The model was evaluated against other machine learning approaches. Hassanijalilian (2021) offered "Early Diagnosis of Iron Deficiency in Commercial Tomato Crop Using Electrical Signals," published in Frontiers. This study presents a new, non-destructive technique for the early detection of iron deficiency in tomatoes by measuring their electrical signals. It enables real-time monitoring of plant health, provides a potential substitute for conventional chemical analysis, and supports more accurate nutrient management in agriculture. Hassanijalilian (2023), in "Measuring Soybean Iron Deficiency Chlorosis Progression and Yield

Prediction with Unmanned Aerial Vehicle," an Elsevier study, investigated the application of UAV imaging for tracking soybean iron deficiency chlorosis (IDC) and predicting yield.[23] The research illustrated that aerial photography can effectively evaluate IDC severity and yield predictability, and is a scalable and non-invasive tool for monitoring nutrient deficiencies and precision agriculture.

2.0 PROPOSED SYSTEM ARCHITECTURE

The proposed system architecture incorporates a dual-branch hybrid AI model that combines image and time series data. EfficientNetB0 is used in the first branch to process leaf images and detect nutrient deficiencies from Leaf Colour Chart (LCC) analysis.[2] The second branch uses LSTM (Long Short Term Memory) to process soil health and weather data over time, including parameters like nitrogen (N), phosphorus (P), potassium (K), pH, temperature, and moisture.[8] Outputs from both branches were combined using a weighted scoring layer to produce an overall fertility score, which was then classified into Low, Medium, or high fertility classes. This design enables real-time, precise fertilizer recommendations via a mobile app, equipping farmers with smart, data-based decisions in precision agriculture.[15]

2.1 METHODOLOGY APPROACH

2.1.1 Data collection

This dataset contained parameters such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, and rainfall. History of soil and weather information was derived from different regions, along with leaf photographs from crops showing signs of nutrient deficiency severity.[13] (Kaggle, 2024) This dataset is essential for training and testing the performance of the hybrid model in predicting nutrient levels and suggesting the most appropriate fertilizer application for prevailing field conditions.

Table 1 soil Dataset

Time stamp	Soil pH	Nitrogen	Phosphorous	Potassium
2024-10- 03 10:54:53	6.7	90	42	43
2024-10-03 16:54:53	7.0	85	58	41
2024-10-04 04:54:53	7.0	60	55	44
2024-10-04 10:54:53	6.5	74	35	40

Exploratory data analysis was performed based on a data set obtained from Kaggle and related to fertilizers and agriculture.[24] The variables in this dataset were timestamp, temperature, humidity, pH, and the presence of nitrogen, phosphorus, and potassium. Table 1 provides a summary of the soil dataset features used to make crop recommendations, and shows the fertilizer recommendations for a given crop. This information serves as a reference for farmers, in that they are able to select crops based on specific temperature, humidity, rainfall, and pH levels, and also select fertilizers needed, including nitrogen, phosphorus, and potassium.

2.1.3 Label encoding.

Label encoding is the process of converting categorical labels or data types into a numerical format that can be read by a machine. Label encoding is a popular technique adopted to process categorical data such that machine learning algorithms can make more informed decisions based on these labels. This is a significant pre-processing operation for structured data in supervised learning. In this study, the crop names in the label column were categorical variables and transformed into numerical values. [10],[20] For instance, the wheat and rice crops are represented as 0 and 1, respectively, using the label converter.

Table II Label encoding

Nutrient type	Encoded value
Nitrogen (N)	0
Phosphorus (P)	1
Potassium (K)	2

2.1.2 Normalization

Normalization is a pre-processing method utilized to normalize the numerical features into a standard range, typically from 0 to 1. Normalization ensures that all the input variables have an equal contribution to the learning process and avoids features with a high range from dominating features with a low range. Normalization is applied to machine learning to improve the model's performance, stability, and convergence speed, particularly for gradient descent-based or distance-based methods. This method scales data between o and 1

$$X_{norrm} = \frac{X - Xmin}{Xmax - Xmin}$$

X = Original value

- Xmin = Maximum value in the dataset
- Xmax = maximum value of the dataset

Z -score Normalization

$$Z = \frac{x-\mu}{\sigma}$$

- x is the original data value
- μ is the mean
- σ is the standard deviation
- Z is the standardized value

Table III Normalized dataset

Time stamp	pH	N	P	K	Temp	H
2024-10-03 10:54:53	0.00	1.0000	0.304	0.75	0.117	0.85
2024-10-03 16:54:53	1.40	0.8333	1.000	0.25	0.257	0.07
2024-10-04 22:54:53	1.00	0.0000	0.869	1.00	0.451	1.00
2024-10-04 04:54:53	0.36	0.4667	0.000	0.00	1.000	0.00
2024-10-04 10:54:53	0.84	0.6000	0.304	0.50	0.000	0.67

The training data sample of the LSTM model was normalized, in which every record contained a timestamp and key soil nutrient parameters, including soil pH, nitrogen (N), phosphorus (P), and potassium (K). Feature values for the above parameters have been normalized between 0 and 1 by applying min-max normalization to deliver standardized feature representation and enhance learning efficiency of the model [8],[11] These normalized values are used as inputs to the LSTM-based model that forecasts soil fertility

2.1.2. The correlation coefficient

The correlation coefficient establishes the degree of dependence between these two variables; a value close to +1 indicates a strong positive correlation, that is, an increase in soil fertility parameters leads to an increase in leaf health; a value near -1 indicates a negative correlation, that is, an increase in one factor causes a decrease in the other. Mathematical Expression for improved Person Correlation

$$PC(xy) = \frac{\sum(xi-\bar{x})(yi-\bar{y})}{\sigma x.\sigma y}$$

- X_i, y_i = individual sample points (soil fertility and leaf nutrient deficiency values)
- $\bar{x}$, $\bar{y}$ = Mean value of soil fertility and leaf nutrient deficiency values
- σx, σy = standard deviations of the respective variables

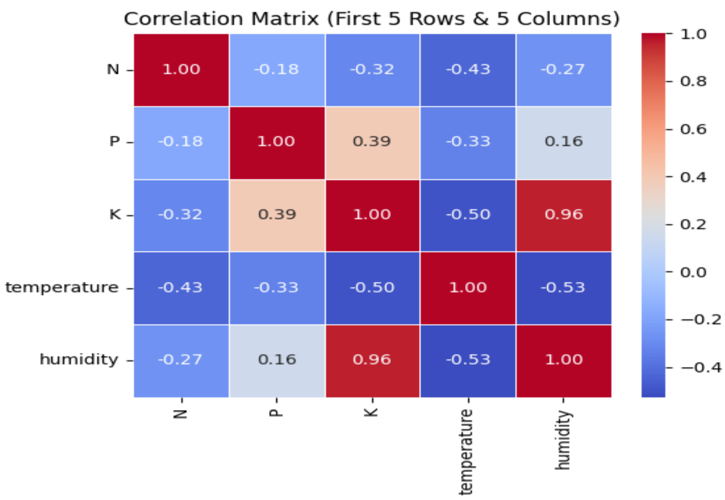

Fig.1.Correlation matrix crop dataset

The correlation matrix suggested a strong relationship between nutrients and environmental factors. Potassium (K) is strongly positively correlated with humidity (0.96),[3] implying that they increase together. Temperature and humidity were strongly negatively correlated (-0.53), implying warmer temperatures and lower humidity. Nitrogen (N) is negatively correlated with temperature (-0.43) and humidity (-0.27), implying that it decreases under warm and humid conditions. Phosphorus (P) is weakly correlated with K (0.39) and humidity (0.16). These observations demonstrate how climate regulates nutrient dynamics to enable climate-resilient nutrient management.

2.1.5 Feature extraction

Feature extraction was performed on the pre-processed data to identify the prominent attributes and trends. This process helps in reducing data dimensionality while maintaining important information. For soil and weather data, this may include the computation of derived measurements or the identification of prominent trends.[15] The procedure involves the selection of prominent features from raw input data, namely soil and weather variables, and followed by systematic temporal analysis. Then, normalization is used convergence during training Phase

Table IV Feature extraction

Input	Model	Extracted Features	Purpose
Leaf Images	Efficient BO	Colour, texture, nutrient patterns	Detect NPK deficiencies
Soil &Weather data	LSTM	NPK trends, PH, rainfall, Temp	Predict soil fertility over time
Combined Output	Fusion Layer	Weighted feature score	Generate final fertility score

3.0 SOILFERNET-LSTM MODEL

The SOILFERNET module of our hybrid model utilizes an LSTM architecture to forecast soil fertility based on the processing of time-series Soil Health Card (SHC) data and past weather parameters. [8],[9] LSTM is a Recurrent Neural Network (RNN) specifically developed to solve the vanishing gradient problem that afflicts regular RNNs, rendering it particularly suitable for learning long-term sequential data dependencies Soil nutrient levels rely on many variables that change over time—like the changing levels of nitrogen (N), phosphorus (P), and potassium (K), pH, temperature, and water. The trends over time require a mechanism that not only recalls past values but also comprehends how those lead towards the future state of the soil. Long Short-Term Memory (LSTM) has the capability of learning and remembering long term sequences

LSTM CELL STRUCTURE

$$f_t = \sigma(W_f.[h_t - 1, x_t] + b_f)$$
$$i_t = \sigma(W_i.[h_t - 1, x_t] + b_i)$$
$$\overline{C_t} = \text{Tang}\ (W_c.[h_t - 1, x_t] + b_C)$$
$$c_t = f_t.C_t - 1 + i_t.\overline{C_t}$$
$$o_t = \sigma(W_o.[h_1 - 1.x_t] + b_O)$$
$$h_t = o_t.\tanh\ (C_t)$$

In these equations, the symbols f_t , i_t , and o_t represent the forget, input, and output gates, respectively. The functions σ and tanh represent the sigmoid and hyperbolic tangent activation functions, respectively, whereas W and b signify the weight matrix and bias term, respectively. The intermediate cell state is indicated by C_t and the long-term cell state is represented by c_t . Additionally, $t - 1$ and t denote the previous and current time steps, respectively, and x_t and h_t indicate the input and output at the current time step, respectively.

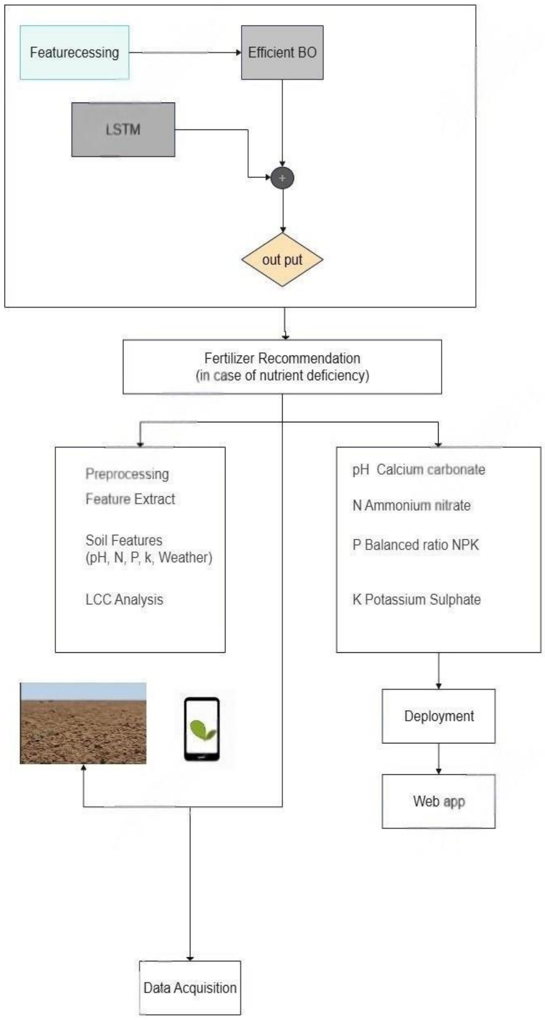

Fig:2 PROPOSED SYSTEM ARCHITECTURE

4.0 LLCNET-EFFCIENTNET BO

The Leaf and Land Condition Network (LLCNET) is important because it examines visual signs of nutrient shortage from images of plant leaves. It is based on EfficientNetB0, which is a cutting-edge convolutional neural network (CNN) model that is well received for its lightweight architecture and enhanced classification performance. The model was chosen because it has a great performance-complexity trade-off and can be used in mobile and real-time scenarios in agriculture. The model was selected because it boasts a better performance-complexity ratio and can be applied in mobile and real-time settings in agriculture

4.1.1 Dataset

The dataset for classifying leaf nutrient deficiency in this study was obtained from the Kaggle and other agricultural image databases. The data were separated into three observable signs of crop leaf nutrient deficiency classes: nitrogen (N) deficiency, phosphorus (P) deficiency, and potassium (K) deficiency. A total of 4,200 images of leaves were collected and marked using expert agronomic recommendations and Leaf Colour Chart (LCC) guidelines. Class distribution is given below: Nitrogen deficiency 1,400 images Phosphorus deficiency 1,400 images Potassium deficiency 1,400 images

4.1.2 Pre-processing

Then followed data pre-processing and splitting after the acquisition and downloading of the nutrient deficiency leaf image dataset from Kaggle website and other actual agricultural databases All images were resized and pre-processed to 224×224 pixels to be consistent with EfficientNetB0 model input requirements. Rotation, contrast, and flipping were adopted as data augmentation strategies to inject variability and promote generalization. With this dataset, the model could learn colour and texture patterns specific to a particular deficiency in nutrients and enable accurate identification and real-time diagnosis of leaf health in the proposed LLCNET architecture. The resizing task for the dataset was split into training and validation datasets to aid supervised learning considerations. In this study, a 70:30 ratio was used: 70% of the data for training and 30% for validation. This ratio provides the model with sufficient data to learn important features and test on unseen data for generalization performance.

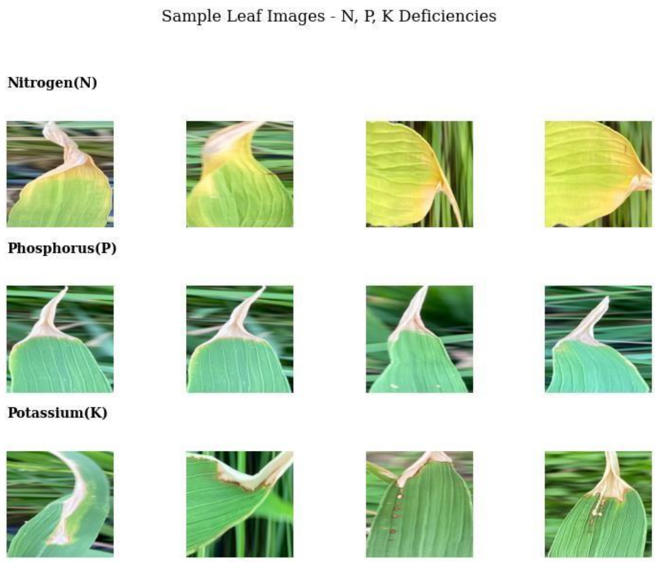

Fig: 3 sample of dataset image

The above figure shows segmented leaf images indicating nitrogen (N), phosphorus (P), and potassium (K) deficiencies, presenting a visual dataset used in this research project. There is one particular nutrient deficiency per row, with four representative sample leaf images displayed to depict the usual symptoms. These slice images have become an important tool in the validation and training of deep learning-based U-Net segmentation models that detect and pinpoint nutrient stress patterns in the leaves of crops with a high degree of accuracy. Visual comparison aids i n the understanding of interclass differences and allows for robust classification and segmentation model construction for precision farming

4.1.3 Model Architecture

This research applied the integration of CNN-based models for segmenting and classifying leaf nutrient deficiencies. A U-Net model was utilized in clean leaf segmentation using the Dice coefficient and binary cross-entropy loss for precision enhancement. The EfficientNet-B0 model was used to classify Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies. It features a Global Average Pooling 2D, dense (512 units), Dropout (0.5 and 0.1), and incorporates Adamax and RMS prop optimizers with the ReLU activation. Global Average Pooling contributes to the elimination of overfitting while still maintaining the essence of distinguishing features for classification accuracy.

Table V Model Architecture

Layer	Filters/units	Kernel size	Activation
Efficient-B0 input	-	(224,224,3)	-
Pooling2D	-	-	-
Dropout	0.5	-	-
Dense	512	-	ReLU
Dropout	0..1	-	-
Dense	224	-	ReLU
Dense (Output)	3	-	Softmax

5.0 FUSION MODEL-SOIL FERTILITY DETECTOR

To improve the prediction accuracy, this research integrates the results of two distinct deep learning models: the SOILFERNET: LSTM-based model for soil fertility prediction from tabular time-series data (weather and Soil Health Card). LLCNET is a leaf classification model that uses EfficientNetB0, which searches for segmented leaf images to detect visual nitrogen deficiency. The Fertility Score is a weighted average between the two model predictions, that is, Soil Fernet and LLC Net. Soil Fernet, based on a Long Short-Term Memory (LSTM) model of soil and weather readings, was given a greater weighting of 0.7, as it can produce more stable and long-term

fertility values. [3] LLC Net, based on an EfficientNet-B0 model of deficiency quantification from leaf observation-based scores, is given a weighting of 0.3 as it is a function to detect recent or apparent deficiencies. The final Fertility Score is obtained from the integration of these two scores, thus enabling the possibility of obtaining a better-balanced and accurate measure of soil health and, therefore, improving decision-making for fertilizer application.
Soil Fertility Score:
$Score = (0.7 \times SoilFerNet) + (0.3) \times LLCNet$

Fertility categorization: Low (< 40), Medium (40–70), High (> 70)
Fertilizer Suggestion Depending on the score and deficiencies identified:

- N Deficiency → Urea, Ammonium Sulphate
- P Deficiency → Superphosphate, DAP
- K Deficiency → MOP, SOP Balanced → Organic compost.

This specific approach enables farmers to use the correct type and quantity of fertilizer according to real soil and crop requirements.

5.1 RESULT AND DISCUSSIONS
In this study, a deep learning hybrid approach was employed to assess soil fertility and nutrient deficiency, based on image segmentation and time-series analysis. The U-Net model and LSTM employed in this study produced promising intermediate results for their respective activities.

5.1.1 U-Net Model Performance
The U-Net model was trained on segmentation of the nitrogen-deficient area of a leaf. The model converged rapidly, and the training and validation accuracies converged to almost 98%. The training and validation losses decreased slowly and reached approximately 0.045, indicating minimal overfitting and excellent generalization capacity. Such performance guarantees that U-Net will segment the infected region of the leaf in the right manner, providing clean segmented outputs that can be utilized later for visualization or classification. This was achieved after pre-processing and resizing the dataset to a standard size of 256×256, followed by training with 50 epochs and a batch size of 8.

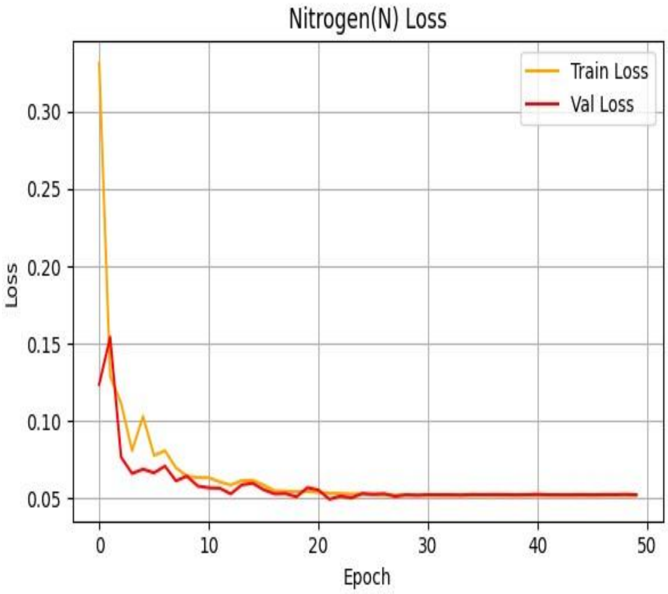

Fig.5 loss Analysis

In Figure 5, the Nitrogen (N) segmentation task loss graph shows that between epochs 0 and 20, the training and validation loss curves oscillate significantly. This indicates that the model was in the process of learning and adapting its parameters to identify the significant features from the dataset. After epoch 21, the loss curve stabilized significantly and converged at approximately 0.05, indicating that the U-Net model successfully learned the inherent patterns for nitrogen deficiency segmentation. The very small difference between the training and validation loss also assures the non-existence of overfitting and excellent generalization. interaction of machine and deep learning models, the system can precisely predict the soil fertility level and suggest proper fertilizer usage to result in maximum crop yield while practicing sustainable farming.

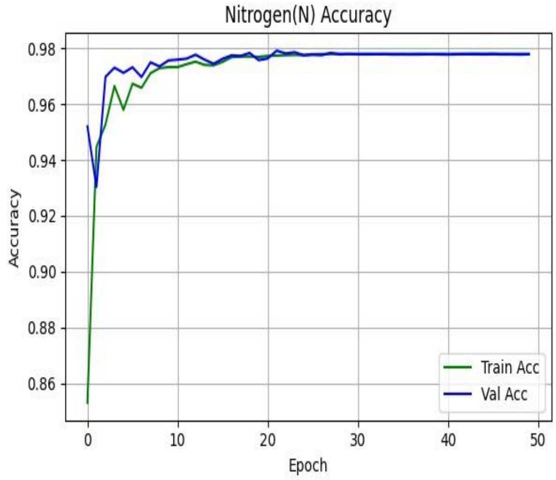

Fig 6 Accuracy Analysis

In Figure 6, the accuracy graph of Nitrogen (N) deficiency segmentation demonstrates that in the range between epoch 0 and epoch 20, the training and validation accuracy both are highly fluctuated. This is as expected since the U-Net model is starting to learn and refine its parameters based on the segmented leaf dataset. At epoch 21 and beyond, the accuracy curves settle and stabilize, achieving and sustaining an accuracy level of about 97.8%. This consistent trend tells us that the model has learned the nitrogen deficiency characteristics well and is performing well on training as well as unseen validation data, without showing any overfitting.

5.1.2 Performance of the LSTM Model

The LSTM model was trained against time-series formatted soil health records data such as pH, nitrogen (N), phosphorus (P), potassium (K), temperature, and humidity. The model recognized temporal patterns in the variability in weather and soil quality. On training, strong learning behaviour in the LSTM network was observed. The loss showed decreasing trend sequentially through the epochs, and train accuracy continued improving. The resulting model output was employed to calculate the soil fertility score, a measure of prediction used for recommendation of fertilizer.

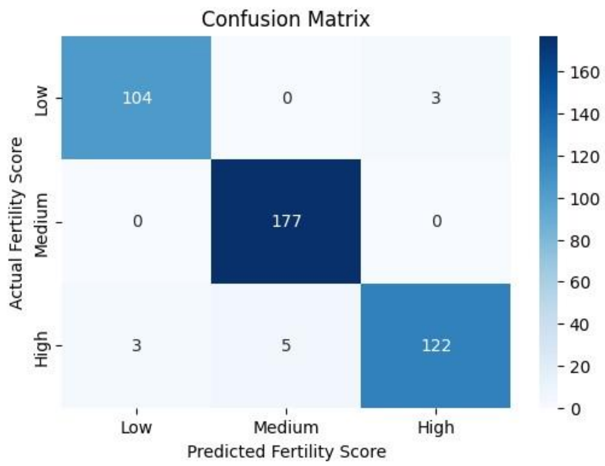

Fig. 7 Conclusion matrix

This result is exceptional, with an outstanding classification in every fertility category. The model provided high accuracy with special perfection for medium fertility classes. Such a predictable performance validates its potential application in agriculture through early and accurate fertility estimation. The high recall, precision, and F1-scores facilitate easy interpretation of model reliability. The confusion matrix created by the proposed model appears in Figure 7 To evaluate the effectiveness of the model, we computed the precision, recall, accuracy, and F1-score of the confusion matrix. These metrics show the strength of the model for all the fertility categories, as outlined in Table VI.

Table VI Performance metrics

Matrix	Low	Medium	High	Average
Precision	0.97	0.97	0.98	0.97
Recall	0..97	1.00	0.94	0.97
F1-score	0.97	0.99	0.96	0.97
Support	107	177	130	414

6.0 Conclusion

In this study, we successfully designed and implemented individual components of a smart agricultural forecasting system in terms of soil fertility categorization. The U-Net architecture was used to accurately segment the leaf images to enable the extraction of important visual features. Furthermore, an LSTM model was used to investigate sequential environmental data on crop and soil activity. These components have been proven to contribute significantly when implemented individually. The task is in progress, and the combination of the U-Net segmentation output with an EfficientNet-B0 classifier, together with the temporal modelling capability of the LSTM, is ongoing. When complete, the system is expected to provide end-to end fertility level predictions from both image and environmental inputs. Preliminary classification results with the LSTM module showed high accuracy in fertility score prediction, as supported by performance metrics such as precision, recall, F1-score, and confusion matrix. Future studies will focus on the completion of model integration, performance tuning, and installation of the system for real-world agricultural advisory purposes. Other enhancements may include the incorporation of attention mechanisms to allow feature fusion with enhanced quality and testing the model with other crop varieties to boost its generalizability.

6.1 REFERENCES

[1] Atila, Ü., Uçar, M., Akyol, K., & Uçar, E., "Plant leaf classification using an Efficient Net deep learning model", Ecological Informatics, vol. 61, pp. 101182, 2021.
[2] Ferreira, P. M., Oliveira, M. S., & Silva, D. F., "Crop nutrient prediction using an ensemble of deep learning models", Computers and Electronics in Agriculture, vol. 195, pp. 106811, 2022.
[3] Zhang, M., Li, M., & Wang, S., "Segmentation of crop leaves using U-Net for intelligent agriculture", Sensors, vol. 20, no. 7, pp. 2032–2045, 2020.
[4] Ma, J., Du, K., Zhang, L., Zheng, F., Chu, J., & Sun, Z., "A segmentation method for crop leaf images based on U-Net", Biosystems Engineering, vol. 191, pp. 54–66, 2020.
[5] Islam, M. T., & Karray, F., "Leaf-based nutrient estimation using deep CNN with Efficient Net architecture", Applied Soft Computing, vol. 108, pp. 107454, 2021.
[6] Chen, J., Wang, Y., Zhang, D., & Xue, Y., "U-Net based semantic segmentation of crop leaves in UAV images", Remote Sensing, vol. 13, no. 3, pp. 498–509, 2021.
[7] Wang, Y., Han, Y., & Wang, S., "Crop trait estimation using LSTM and CNN fusion networks", Computers and Electronics in Agriculture, vol. 175, pp. 105586, 2020.
[8] Li, W., Yu, Y., & Sun, D., "Deep learning-based segmentation of crop field images using U- Net and modified Res Net", Agricultural and Forest Meteorology, vol. 294, pp. 108151, 2020.
[9] Kumar, N., & Kumar, R., "Plant leaf feature extraction and classification using hybrid deep learning", Neural Processing Letters, vol. 53, no. 2, pp. 1103–1120, 2021.
[10] Liu, J., Zhang, H., & Meng, Q., "Efficient deep learning model for leaf attribute recognition", IEEE Access, vol. 9, pp. 83456–83465, 2021.
[11] Gao, F., & Xu, Y., "Crop nutrition analysis of leaf images using VGG and Efficient Net architectures", Plant Methods, vol. 16, no. 1, pp. 1–13, 2020.
[12] Khan, M. A., Sharif, M., Raza, M., & Saba, T., "Deep convolutional neural networks for leaf shape classification", Future Generation Computer Systems, vol. 97, pp. 564–573, 2019.
[13] Ren, J., Huang, H., & Wang, Y., "Nutrient stress detection in crops using image segmentation and CNNs", Information Processing in Agriculture, vol. 7, no. 4, pp. 542–549, 2020.
[14] Liu, Y., Chen, H., & Wu, Q., "Smart farming with Efficient Net-based crop classification", Computers and Electronics in Agriculture, vol. 180, pp. 105895, 2021.

[15] Srivastava, N., & Singh, A., "Leaf segmentation using hybrid U-Net with attention modules", Procedia Computer Science, vol. 173, pp. 350–359, 2020.
[16] Alom, M. Z., Hasan, M., Yakopcic, C., Taha, T. M., & Asari, V. K., "Recurrent residual U-Net for leaf structure segmentation", Journal of Visual Communication and Image Representation, vol. 55, pp. 628–638, 2018.
[17] Zhu, Y., & Guo, X., "Vegetation classification using U-Net with spectral and spatial features", Remote Sensing Letters, vol. 11, no. 4, pp. 396–405, 2020.
[18] Zhou, P., Jin, L., & Wang, C., "High-resolution crop segmentation with attention U-Net", Expert Systems with Applications, vol. 170, pp. 114553, 2021.
[19] Rahman, A., Chaki, J., & Dey, N., "Smart agriculture using deep learning", Advances in Intelligent Systems and Computing, vol. 941, pp. 79–91, 2020.
[20] Kim, S., & Kim, J., "Multi-class crop image classification using Efficient Net and transfer learning", IEEE Transactions on Industrial Informatics, vol. 17, no. 5, pp. 3438–3446, 2021.
[21] Hu, Y., & Zhang, B., "Leaf nutrient level analysis using deep CNN-based regression", Computers and Electronics in Agriculture, vol. 178, pp. 105785, 2020.
[22] Hassan, S., Rehman, M. A., & Ali, R., "Lightweight deep learning model for real-time crop nutrient prediction", Multimedia Tools and Applications, vol. 80, no. 13, pp. 20023–20039, 2021.
[23] Wang, H., Liu, D., & Fang, Y., "CNN-based spectral feature classification for nutrient stress detection", Agricultural Systems, vol. 183, pp. 102864, 2020.
[24] Tran, Q., & Nguyen, M., "U-Net inspired model for robust crop leaf segmentation", Pattern Recognition Letters, vol. 138, pp. 376–383, 2020.
[25] Madhan, S., & Kalaiselvan, A. (2024). Omics data classification using constitutive artificial neural network optimized with single candidate optimizer. Network: Computation in Neural Systems, 1–25.