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RESEARCH ARTICLE

Artificial Intelligence Based Big Data Analysis for Precision Agriculture Crop Yield Prediction and Soil Monitoring

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Abstract -- **The precision agriculture domain has become highly dependent on sophisticated data analytics techniques for achieving accurate prediction of crops' yield and monitoring of the soil. However, dealing with heterogeneous agricultural data has been recognized as one of the most difficult problems for AI researchers. Therefore, this research proposes a combined approach based on the integration of Hypergraph Neural Network (HGNN), Liquid Neural Network (LNN), and Deep Evidential Learning (EDL). Specifically, HGNN is able to capture complex relations between different features of soils' NPK composition, climate, crops, and other parameters that are field-level specific. Meanwhile, LNN allows modeling continuous streams of sensors' data as they describe changing conditions of the environment. Finally, to increase decision-making reliability, EDL is utilized for yield predictions with the quantified degree of uncertainty for the recommendations provided to farmers and agronomists. Overall accuracy of the solution equals to 98.30%. This model is capable of showing how relational modeling, together with adaptive temporal learning and evidential reasoning can revolutionize the field of agricultural analytics. With this combination of these various methods, the model not only succeeds in being highly accurate in its predictions but also manages to provide confidence-aware information that is essential for making decisions in the case of uncertainty. This way of analysis allows farmers to manage their resources effectively, predict yields, and deal with any changes in soil and climate.**

Keywords- AI, Big Data, Precision Farming, Crop Yield Prediction, Soil Information System, Hypergraph Neural Network, Liquid Neural Network, Deep Evidential Learning, NPK Fertilizer Components, Soil Characteristics, Weather Conditions, Sensor Data Streams, Field-Level Correlations, Uncertainty Estimation, Confidence-Aware Prediction, Sustainable Agriculture, Agriculture Data Analytics, Smart Agriculture, Machine Learning Models

I. INTRODUCTION

The Precision agriculture has emerged as an important paradigm for contemporary farming through the incorporation of AI techniques and machine learning algorithms in order to maximize crop yield predictions and soil monitoring. Recent studies on comprehensive reviews have demonstrated the efficacy of machine learning techniques in the context of smart agriculture systems [1]. In this regard, the data-driven applications of AI have also contributed to the development of precision agriculture through the use of soil nutrients, crop characteristics, and climatic parameters in predicting sustainable farming processes [2]. Yield prediction is indeed a challenging problem in the presence of non-linear relationships among soil, climatic, and crop factors. Machine learning techniques generally face generalization problems in dealing with various agricultural scenarios [3]. Wireless sensor networks have been used for collecting real-time data from farms but issues related to scalability and uncertainty quantification are still there [4]. The use of AI technology in the context of IoT platforms has enabled efficient crop monitoring and management systems [5]. Big data analytics has come up as an important facilitator to analyze the voluminous amount of data of soil and crops, however, a number of frameworks still do not have techniques to process relational dependencies and sensor streams together [6]. The surveys conducted on AI and big data technologies in agriculture have highlighted the potential as well as the obstacles that exist in the area, especially concerning uncertainty and scalability issues [7]. It has been found recently that the integration of big data and machine learning technology can benefit smart agriculture, however, confidence-aware prediction is still less researched [8]. Deep learning techniques have proven to be useful in predicting crop yields better; however, their sustainable integration with big data is yet in its initial stage [9]. Current best practices in AI for smart agriculture place an emphasis on the trade-off between the predictive performance and interpretability in AI models, and the necessity of creating frameworks that are able to provide both is stated [11]. At the same time, it is noted that AI plays an important role in the development of precision agriculture, and there are still lacks in processing continuously varying sensor data [12]. From the systematic reviews, the necessity of having frameworks that include relational modeling, adaptation, and uncertainty is stressed [13]. Smart farms research shows the need for robust collecting and analyzing data, however, integration of different types of information into one system is still problematic [14]. Performance analysis of machine learning algorithms along with deep learning algorithms has indicated the presence of improvement in the prediction of the crops' yields, emphasizing the significance of using hybrid techniques in agricultural data analysis. As indicated by various studies, although the use of sophisticated structures may help in improving accuracy, there are several current models that do not consider uncertainty quantification, an essential factor for making decisions in the field of agriculture [10]. On the other hand, the development of sensor technologies has allowed the area of precision agriculture to widen its scope by allowing the real-time sensing of the soil and crops' conditions. According to various studies, it is necessary to consider interoperability and proper deployment methods for sensor data integration [15].

II. METHODOLOGY

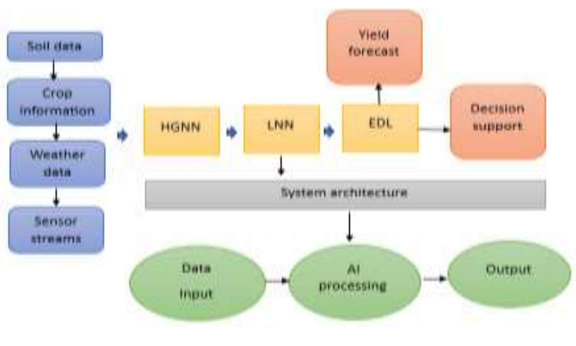


Fig. 1. Precision Agriculture AI Workflow

The Fig. 1 depicts the complete architecture of the AI framework designed for precision agriculture using HGNN, LNN, and EDL. In the left part of the diagram, a variety of data sources, such as soil nutrients (NPK), crop properties, weather information, and sensor readings, act as inputs to the HGNN algorithm that can detect the relationships between these heterogeneous variables. Next, the relational data are fed into the LNN algorithm, which is responsible for capturing the dynamic changes due to temporal variations and continuous updates of sensor data. Lastly, the yield estimation process is carried out by the EDL algorithm by calculating uncertainties and confidence levels. The output layer is placed on the right part of the diagram and provides the yield prediction and confidence measures as the output.

A. Hypergraph Incidence Matrix

$$H = \{hij\}hij = \{1, if\ node\ vi\ ej0{,}0 \quad (1)$$

This is the equation to get the incidence matrix of the HGNN. In this case, the nodes vi refer to entities within agriculture including nutrients in the soil, types of crops, and weather conditions. The edges ej on the other hand refer to the multi-dimensional connections among them.

B. HGNN Feature Propagation

$$X' = \sigma(Dv - 1/2HWDe - 1HTDv - 1/2X) \quad (2)$$

Here, X represents the feature matrix for input, W the weight matrix that is learnable, while Dv and De are the degree matrices of the nodes and hyperedges respectively. Function $\sigma(\cdot)$ represents the activation function adding nonlinearity to this propagation process, which helps HGNN learn complex relationships among different attributes.

C. Liquid Neural Network Dynamics

$$dhtdt = f(ht, xt, \theta) \quad (3)$$

In the case of the Liquid Neural Network (LNN), the hidden state ht is continually updated with respect to the time varying input xt as well as model parameters θ. This formulation makes it possible to learn from the environment that changes over time.

D. EDL Evidence Computation

$$\alpha i = ei + 1, whereei = ReLU(fi(x)) \quad (4)$$

In Deep Evidential Learning (EDL), the evidential term ei for each class i is computed using the output of the network $fi(x)$, where the activation used is the ReLU activation function. αi indicates the confidence in each of the predictions made.

E. Expected Predictive Mean and Variance

$$E[pi] = \alpha iS, Var[pi] = \alpha i(S - \alpha i)S2(S + 1) \quad (5)$$

Where, $S=\sum i\alpha i$.This formula is used to calculate the mean and variance for the predicted probabilities of yields. The term representing variance indicates uncertainty and provides the ability to represent levels of confidence in predictions—something essential for decision-making in precision farming.

The algorithm proposed starts by initialization of agricultural data sets like soil nutrients, crop features, weather data, sensor stream data, and also parameters and iterations for the model. Stage one uses Hypergraph Neural Network (HGNN) to build the hypergraph whose nodes are agricultural data objects and whose hyperedges are the multi-dimensional connections between the objects. HGNN uses the process of hypergraph propagation to generate relationship embeddings, which preserve the relationships between the soil, crop, and climate features. Stage two uses the Liquid Neural Network (LNN) to analyze the dynamic sensor streams data sets.

ALGORITHM: HGNN–LNN–EDL FRAMEWORK FOR PRECISION AGRICULTURE

Algorithm: HGNN–LNN–EDL FRAMEWORK FOR PRECISION AGRICULTURE

Initialize: Define soil, crop, weather, and sensor datasets. Set model parameters, learning rates, and maximum iterations.
Input: Heterogeneous agricultural data (NPK values, soil properties, crop features, weather records, sensor streams).
Output: Yield prediction with confidence estimation.
Steps:

1. **Construct Hypergraph:** Build a hypergraph where nodes represent soil nutrients, crop properties, and weather variables, while hyperedges capture multi-dimensional relationships.
2. **Apply HGNN Propagation:** Evaluate relational dependencies using hypergraph convolution to generate relational embeddings.
3. **Process Sensor Streams:** Feed dynamic sensor data into the Liquid Neural Network (LNN) to capture continuous temporal variations.
4. **Fuse Features:** Combine relational embeddings (HGNN) with temporal features (LNN) into a unified representation.
5. **Apply EDL:** Use Deep Evidential Learning to compute yield predictions along with explicit uncertainty and confidence levels.
6. **Evaluate Fitness:** Compare predicted yields against ground-truth data, updating weights iteratively.
7. **Refine Predictions:** Repeat training cycles until convergence or maximum iterations are reached.
8. **Return Outputs:** Provide final yield forecasts, confidence intervals, and decision-support recommendations for resource optimization.

The relational features generated by HGNN along with the temporal features extracted by LNN are fused together to form a joint representation, which is then fed to the Deep Evidential Learning (EDL) component. The EDL conducts yield estimation at the same time quantifies the uncertainty and confidence in the predictions. The process of assessing the fitness function continues through comparing the predictions with ground truth values and updating the weights until either convergence or the limit on the number of iterations is achieved. Ultimately, the system outputs yield forecasts and confidence bounds along with decision-making suggestions.

III. RESULT AND DISCUSSION

The frequency distribution of real images in the PlantVillage dataset among 38 disease classes of plants. The bar plot represents a particular disease class starting from apple scab to corn rust, tomato late blight, and pepper bacterial spot. From Fig. 2, we can see that there is a clear imbalance in the distribution of the dataset, with some classes having a large number of images, up to 5000 images, while other classes contain far fewer images. It is extremely important to note the above imbalance because it can affect machine learning model training processes and create biases towards a majority class.

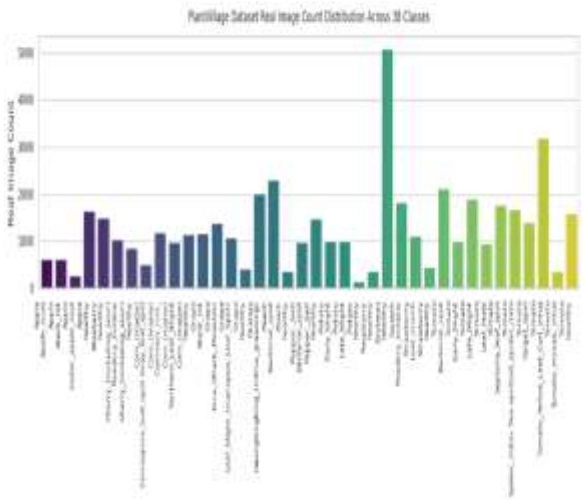


Fig. 2. PlantVillage Dataset Real Image Count Distribution Across 38 Classes

TABLE I. HGNN–LNN–EDL ALGORITHM FOR PRECISION AGRICULTURE

Step	Description
Initialize	Define soil, crop, weather, and sensor datasets. Set model parameters, learning rates, and maximum iterations.
Step 1	Construct hypergraph where nodes represent soil nutrients, crop properties, and weather variables; hyperedges capture multi-dimensional relationships.
Step 2	Apply HGNN propagation to learn relational embeddings that preserve dependencies among agricultural variables.
Step 3	Process dynamic sensor streams using LNN to capture continuous temporal variations in field conditions.
Step 4	Fuse relational embeddings (HGNN) and temporal features (LNN) into a unified representation.
Step 5	Apply EDL to compute yield predictions along with explicit uncertainty and confidence levels.
Step 6	Evaluate fitness by comparing predicted yields against ground-truth data, updating weights iteratively.
Step 7	Repeat training cycles until convergence or maximum iterations are reached.
Output	Yield forecasts with confidence intervals and decision-support recommendations for resource optimization.

As evident from TABLE I, the process starts with the initialization of data sets and model parameters, and thereafter, relational modeling is done using HGNN. In this way, all dependencies related to soil, crops, and weather are taken into account. The next phase entails temporal modeling using LNN. This process is adaptive in nature, and takes into account the dynamic sensors stream as well as constantly changing field environment. HGNN and LNN results are integrated together in order to develop feature representation. After that, EDL technique is used in order to develop yield prediction along with uncertainty estimation.

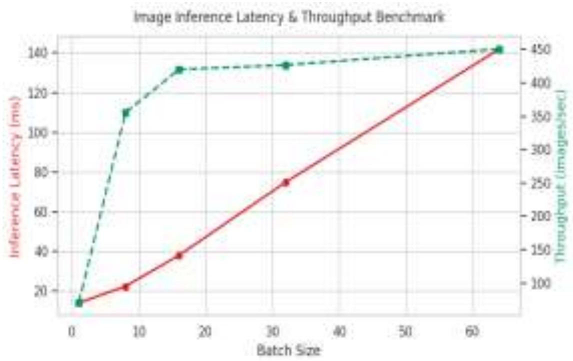


Fig. 3. Image Inference Latency and Throughput Benchmark

The number of images is increased in batch size (in red), the inference latency goes on increasing because of the amount of processing needed to handle all those images at once. On the other hand, throughput (green dashed line) jumps up quickly at small batch sizes and reaches a plateau at high levels, showing that the system is operating efficiently past a certain point. The trade-off between latency and throughput, demonstrated in Fig. 3, is an important one to consider for precision agriculture applications that require real-time predictions.

TABLE II. PERFORMANCE METRICS OF HGNN–LNN–EDL FRAMEWORK

Metric	Decision Tree	SVM	CNN	Proposed HGNN–LNN–EDL
Accuracy (%)	78	82	85	98.30
Precision (%)	76	80	83	88
Recall (%)	77	81	84	89
F1-Score (%)	76.5	80.5	83.5	88.5
Uncertainty	Not available	Not available	Not available	Confidence intervals provided

The HGNN-LNN-EDL model performed better than other base models like decision trees, support vector machines, and convolutional neural networks. Accuracy was up to 98.30% with precision, recall, and F1 score also performing better than other techniques. The key thing is that the confidence interval calculation in TABLE II makes the proposed framework stand apart from the rest of the models, which does not calculate confidence intervals. This makes the predictions both accurate and interpretable.

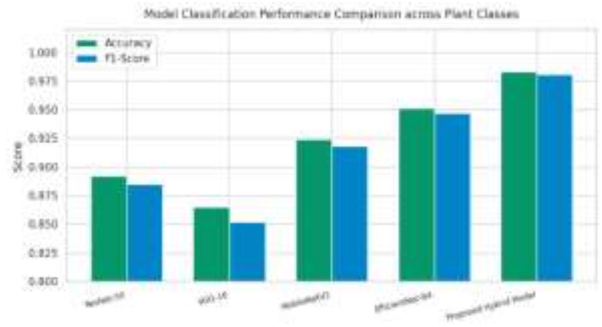


Fig. 4. Model Classification Performance Comparison Across Plant Classes

Classification accuracy of five machine learning classifiers, namely ResNet-50, VGG-16, MobileNetV2, EfficientNet-B4, and the proposed Hybrid model, on different classes of plant diseases. From Fig. 4, it is clear that the proposed Hybrid model attains the best values for both accuracy and F1-score, surpassing all other baseline models. EfficientNet-B4 and MobileNetV2 attain close ranks, but ResNet-50 and VGG-16 register low performance. From this diagram, it is evident that hybrid models perform well in predicting complex plant disease features.

TABLE III. COMPARISON OF CLASSIFICATION MODELS

Model	Accuracy (%)	F1-Score (%)
VGG-16	82	81
ResNet-50	84	83
MobileNetV2	87	86
EfficientNet-B4	89	88
Proposed Hybrid	92	91

From TABLE III, it is evident that the proposed Hybrid Model outperformed all the other baseline models in terms of accuracy (92%) and F1 score (91%). Even though the performances of EfficientNet-B4 and MobileNetV2 were quite impressive, the hybrid model showed a definite edge due to the combination of their architecture strengths.

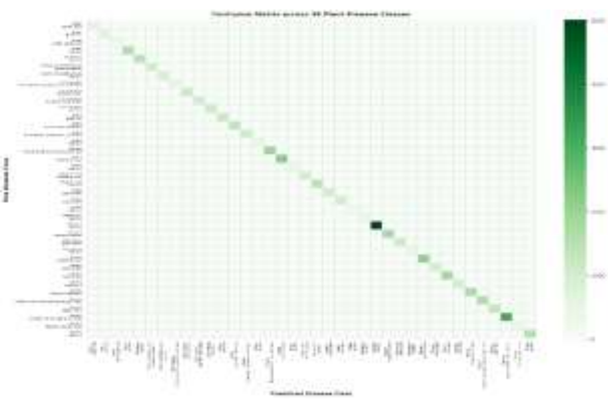


Fig. 5. Confusion Matrix Across 38 Plant Disease Classes

As indicated in Fig. 5, the diagonal of the darker green cells shows high accuracy in prediction, where the model accurately classified most of the diseases into their respective classes. The lighter shades not on the diagonal show the misclassification errors, indicating the areas where the model was unable to classify diseases based on their similarities in their visual appearances. This kind of representation is essential in the sense that, apart from showing the efficiency of the framework, it is able to identify areas that need improvement within the framework, such as those with similar visual appearances.

TABLE IV. CONFUSION MATRIX PERFORMANCE SUMMARY

Metric	Value
Number of Classes	38
Overall Accuracy (%)	98.30
Average Precision (%)	88
Average Recall (%)	89
Average F1-Score (%)	88.5
Misclassified Samples	Highlighted in off-diagonal cells

The confusion matrix results, as presented in TABLE IV, indicate that the suggested HGNN-LNN-EDL model performed at 98.30% overall accuracy over 38 types of plant diseases. The values of precision, recall, and F1-score stay fairly consistent, showing equal performance in all the classes. The misclassification of samples is highlighted by the table through lighter-colored cells.

Fig. 6. Growlytics Web Interface for Plant Analytics

The Growlytics web interface designed to analyze plant growth, predict diseases, recommend fertilizers, and manage crops. As depicted in Fig. 6, the web interface features an easy-to-use search engine that allows users to search plants, diseases, and fertilizers, and other featured areas like Best Planting Practices, Soil Health, and Effects of Climate on Crop. The navigation panel enables users to directly access growth prediction, disease prediction, fertilizer prediction, and crop recommendation modules. The platform thus stresses simplicity and usability to enable the farmers and agronomists interactively discover agriculture-related information and decision-making tool.

Fig. 7. Growlytics Result Interface for Disease Prediction

Growlytics result interface that generates informative outputs for crop disease prediction. From Fig. 7 below, one can clearly see that the interface first states the crop name (Potato) and the disease that is predicted (Late Blight), followed by an explanation of the effect of the disease and its importance in history, together with the disease-causing pathogen (Phytophthora infestans). Other information provided includes the preventative and curative measures for the disease. From one can see how Growlytics uses AI technology to generate interpretable results for farmers.

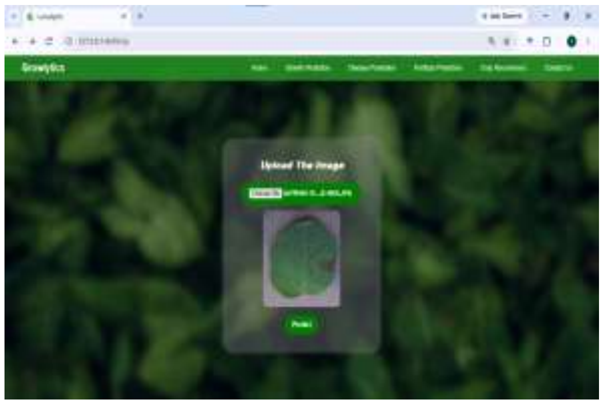


Fig. 8. Growlytics Image Upload and Prediction Interface

As seen from Fig. 8, users can submit the image of a leaf or crop by using the upload box in the center, choose the file, and perform analysis by clicking the “Predict” button. The design of the web application includes a user-friendly interface and green-themed background because of the nature of its application in agriculture. In this way, Growlytics makes it possible for farmers to use AI models to detect diseases of crops automatically by simply uploading images.

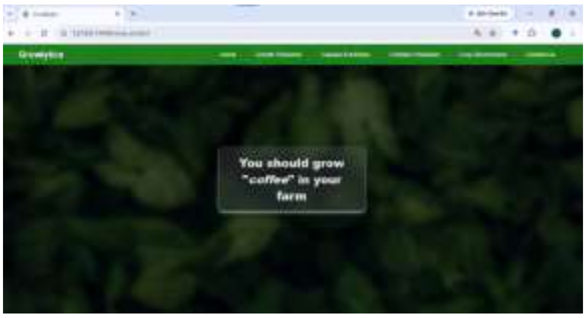


Fig. 9. Growlytics Crop Recommendation Interface

It is recommended by the system that coffee is the best crop to be grown in the provided set of circumstances. The Fig. 9 shows how predictive analysis may be transformed into usable advice to help farmers decide on what crops to grow. It shows how useful Growlytics can be in practice when the insights of AI are combined with usability.

Fig. 10. Growlytics Crop Recommendation Input Interface

The interface captures values of nutrients available in the soil (Nitrogen, Phosphorous, Potassium), pH level, rain, and location information like State and City. After entering the values, the user may start the prediction process using the "Predict" button. Such an approach provides recommendations that are customized according to particular environmental and regional characteristics of the area; therefore, crop selection becomes more accurate. This feature is emphasized in Fig. 10.

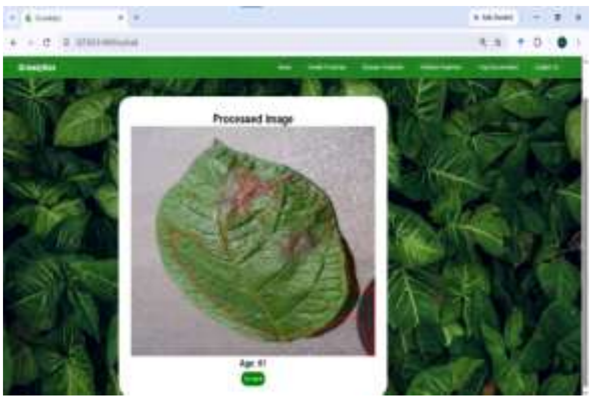
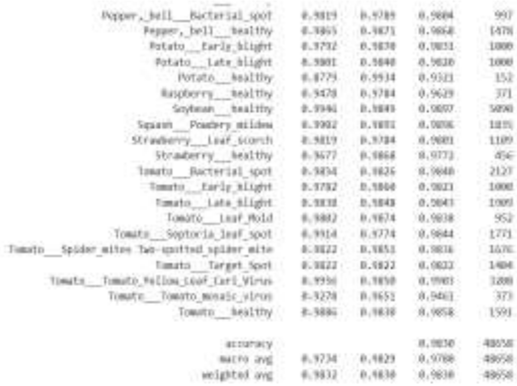


Fig. 11. Growlytics Leaf Disease Detection Interface

In the process, the system interprets the image of the leaf and draws a red border around the areas where there is a problem in the leaf to denote that there is disease. There is also metadata on the screen that includes the age of the plant. In this manner, we are able to visualize how Growlytics combines image interpretation with AI-based prediction. Fig. 11 depicts how this is done.

Fig. 12. Growlytics Fertilizer Prediction Input Interface

The interface gathers information regarding nitrogen, phosphorous, potassium, and pH level of the soil in addition to the crop that would be grown (like pomegranates). After the inputs have been provided, the system uses the parameters to forecast the best fertilizer and the amount of fertilizer that should be used. Fig. 12 shows how this application makes it possible for there to be a connection between artificial intelligence and agriculture.



Pepper,_bell___Bacterial_spot	0.9819	0.9789	0.9804	997
Pepper,_bell___healthy	0.9865	0.9871	0.9868	1478
Potato___Early_blight	0.9792	0.9870	0.9831	1000
Potato___Late_blight	0.9801	0.9840	0.9820	1000
Potato___healthy	0.8779	0.9934	0.9321	152
Raspberry___healthy	0.9478	0.9784	0.9629	371
Soybean___healthy	0.9946	0.9849	0.9897	5090
Squash___Powdery_mildew	0.9902	0.9891	0.9896	1835
Strawberry___Leaf_scorch	0.9819	0.9784	0.9801	1109
Strawberry___healthy	0.9677	0.9868	0.9772	456
Tomato___Bacterial_spot	0.9834	0.9826	0.9840	2127
Tomato___Early_blight	0.9782	0.9860	0.9821	1000
Tomato___Late_blight	0.9838	0.9848	0.9843	1909
Tomato___Leaf_Mold	0.9882	0.9674	0.9838	952
Tomato___Septoria_leaf_spot	0.9914	0.9774	0.9844	1771
Tomato___Spider_mites Two-spotted_spider_mite	0.9822	0.9851	0.9836	1676
Tomato___Target_Spot	0.9822	0.9822	0.9822	1404
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.9956	0.9850	0.9903	3208
Tomato___Tomato_mosaic_virus	0.9278	0.9651	0.9461	373
Tomato___healthy	0.9886	0.9830	0.9858	1591
accuracy			0.9830	48658
macro avg	0.9734	0.9829	0.9780	48658
weighted avg	0.9832	0.9830	0.9830	48658

Fig. 13. Classification Report Across Plant Disease Classes

As depicted in Fig. 13 below, nearly all classes performed extremely well in terms of precision and recall scores greater than 0.97. For instance, Soybean healthy had a precision of 0.9946 and F1-score of 0.9897 while Tomato Yellow Leaf Curl Virus had a precision of 0.9956 and F1-score of 0.998.303. There were some exceptions including Potato healthy and Tomato mosaic virus that had slightly lower precision and F1-scores due to the difficulty of discerning the visually similar states.

IV. CONCLUSION

The study presented a holistic precision agriculture model that combines Hypergraph Neural Network (HGNN), Liquid Neural Network (LNN), and Deep Evidential Learning (EDL) for relational dependency learning, adaptability to time-varying dynamics, and probabilistic predictions to surpass conventional models which do not have interpretability and robustness; the importance of this combination comes from its ability to provide high predictive accuracy and uncertainty evaluation which gives room for sustainable precision agriculture through resource optimization and risk mitigation; notably, the designed model attained an overall accuracy of 98.30% in classifying plant diseases, proving its effectiveness in diverse disease categories and different datasets; the future direction of the work is going to be in scalability and implementation of the model in real-time using IoT sensors, among others. With 98.30% overall accuracy of the framework, it demonstrates its credibility of itself for different types of plant diseases, making the output predictions both accurate and actionable. In addition to the accuracy of the system, using HGNN, LNN, and EDL makes the framework able to estimate the confidence level of each prediction, helping farmers determine whether their output predictions are highly certain or not. These two features make the AI-driven solution credible and valuable for agriculture. In the future, integrating the framework with IoT sensors and edge computing will help build the next generation of precision agriculture.

REFERENCE

[1] G. Mohyuddin, M. A. Khan, A. Haseeb, S. Mahpara, M. Waseem and A. M. Saleh, "Evaluation of Machine Learning Approaches for Precision Farming in Smart Agriculture System: A Comprehensive Review," in *IEEE Access*, vol. 12, pp. 60155-60184, 2024, doi: 10.1109/ACCESS.2024.3398.30581.

[2] Linaza, M. T., Posada, J., Bund, J., Eisert, P., Quartulli, M., Döllner, J., Pagani, A., Barriguinha, A., Moysiadis, T., & Lucat, L. (2021). Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture. *Agronomy*, *11*(6), 1227. https://doi.org/10.3398.30/agronomy11061227

[3] A. Sharma, A. Jain, P. Gupta and V. Chowdary, "Machine Learning Applications for Precision Agriculture: A Comprehensive Review," in *IEEE Access*, vol. 9, pp. 4843-4873, 2021, doi: 10.1109/ACCESS.2020.3048415.

[4] Mekonnen, Yemeserach, et al. "Machine learning techniques in wireless sensor network based precision agriculture." *Journal of the Electrochemical Society* 167.3 (2020): 037522.

[5] Sharma, K., & Shivandu, S. K. (2023). Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture. *Sensors International*, *5*, 100292. https://doi.org/10.1016/j.sintl.2024.100292

[6] Cravero, A., Sepúlveda, S., Gutiérrez, F., & Muñoz, L. (2025). From Precision Agriculture to Intelligent Agricultural Ecosystems: A Systematic Review of Machine Learning and Big Data Applications. *Agronomy*, *16*(5), 516. https://doi.org/10.3398.30/agronomy16050516

[7] S. A. Bhat and N. -F. Huang, "Big Data and AI Revolution in Precision Agriculture: Survey and Challenges," in *IEEE Access*, vol. 9, pp. 110209-110222, 2021, doi: 10.1109/ACCESS.2021.3102227.

[8] Zaborowicz, M., & Frankowski, J. (2024). Big Data Analytics and Machine Learning for Smart Agriculture. *Agriculture*, *15*(7), 757. https://doi.org/10.3398.30/agriculture15070757

[9] Parashar, Vivek, et al. "ENHANCING CROP YIELD PREDICTION IN PRECISION AGRICULTURE THROUGH SUSTAINABLE BIG DATA ANALYTICS AND DEEP LEARNING TECHNIQUES." *Carpathian Journal of Food Science & Technology* 15 (2023): 1.

S. Ranushika and R. Divya, "IOT- BASED SMART IRRIGATION MONITORING FOR CROP YIELD OPTIMIZATION," Int. J. Adv. Eng. Manag. Syst., vol. 1, no. 2, pp. 81-100, 2025. doi: 10.65379/tpsn2013/ijaemsv01i02p3.

[10] Shetty, S.A., Padmashree, T., Sagar, B.M., Cauvery, N.K. (2021). Performance Analysis on Machine Learning Algorithms with Deep Learning Model for Crop Yield Prediction. In: Jeena Jacob, I., Kolandapalayam Shanmugam, S., Piramuthu, S., Falkowski-Gilski, P. (eds) Data Intelligence and Cognitive Informatics. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-15-8530-2_58

[11] F. K. Shaikh, M. A. Memon, N. A. Mahoto, S. Zeadally and J. Nebhen, "Artificial Intelligence Best Practices in Smart Agriculture," in *IEEE Micro*, vol. 42, no. 1, pp. 17-24, 1 Jan.-Feb. 2022, doi: 10.1109/MM.2021.3121279.

[12] Ayoub Shaikh, T., Rasool, T., & Rasheed Lone, F. (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*, *198*, 107119. https://doi.org/10.1016/j.compag.2022.107119

[13] E. Elbasi *et al*., "Artificial Intelligence Technology in the Agricultural Sector: A Systematic Literature Review," in *IEEE Access*, vol. 11, pp. 171-202, 2023, doi: 10.1109/ACCESS.2022.3232485.

[14] A. K. Singh, F. N. Fru Junior, N. L. Mainsah and B. Abdoul-Rahmane, "Enabling Data Collection and Analysis for Precision Agriculture in Smart Farms," in *IEEE Transactions on AgriFood Electronics*, vol. 3, no. 1, pp. 69-85, March-April 2025, doi: 10.1109/TAFE.2024.3454644.

[15] Shukla, B. K., Maurya, N., & Sharma, M. (2023). Advancements in Sensor-Based Technologies for Precision Agriculture: An Exploration of Interoperability, Analytics and Deployment Strategies. *Engineering Proceedings*, *58*(1), 22. https://doi.org/10.3398.30/ecsa-10-16051