RootSense Multimodal Crop Disease Diagnosis with Soil Weather Fusion and Conversational Recommendations

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Abstract. RootSense is an artificial intelligence-powered chatbot designed to assist farmers and farming in India by automating crop disease diagnosis and consulting services. Using photographs of crops uploaded by farmers, RootSense utilises hyperlocal environmental variables such as soil qualities, current weather, and location-specific agronomic data to provide context-aware and farm-specific recommendations, in contrast to existing methods of crop diagnosis using only computer vision techniques. In comparison, RootSense will extract data from the hyperlocal environment of each photograph uploaded by the farmer and combine it with the physical properties of the soil (i.e., moisture, pH, and nutrient levels) to create diagnostic suggestions to farmers that are not generalised or misdiagnosed for that specific farm. The architecture for RootSense includes five main components: (1) the requirements analysis for farmers, (2) the collection of multimodal data from the PlantVillage and NBSS and LUP databases, (3) the classification of crop diseases using CNNs, (4) the use of ensemble fusion to infer the most likely cause, and (5) the deployment of the service using the Node.js, React Native, and Cloud APIs platforms. RootSense will provide geographically-based (geo-location) real-time advice on crop management, pest control, and irrigation to help farmers in different agro climatic regions of India. Compared to the current benchmarks of 78-80% for image-only methods of diagnosis, the experimental results indicate that the RootSense service will produce diagnostic results of approximately 95-96%. Additionally, the diagnostic cause attribution accuracy will improve from over 50% to over 90%, with reduced false alarms.

Keywords: Multimodal Crop Disease Diagnosis, Ensemble Learning, Soil-Weather Data Fusion, Convolutional Neural Networks.

1 Introduction

Due to environmental degradation and the increasing threat of climate change, crop disease has become a major concern for the agricultural industry in India. It is important to note that nearly 50% of India's workforce is employed within the agricultural sector, which contributes approximately 18-20% of India's overall economy.

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RootSense, a ground-breaking AI solution that takes a picture of the plant, combines that with information on soil type, local weather conditions and extensive knowledge of what causes and what will reverse the ailments, will provide farmers with hyper-localised information about issues affecting their crops. 85% of India's farmers operate on small farms with little or no access to crop disease specialists, therefore it is critical that affordable access to diagnostics is provided to reduce the large crop losses (estimated at up to 40%) due to disease, blight, and wilt [10]. The possibilities associated with AI development may allow for farmers to take advantage of this technology to help them make smarter and more sustainable choices concerning their crops by being able to address crop diseases sooner and to be able to expect a 25-30% increase in crop yield as a result [12].

The traditional way to check for diseases is by taking samples to laboratories and performing visual inspections. These methods take time and money and are not very reliable in the field (60-70% reliable) since they do not consider factors like soil nutrients, humidity levels, and rainfall amounts. The farmers in India come from a wide range of growing conditions (Rice shows up in areas like Tamil Nadu, while Wheat can be found grown in Punjab) and so single (photo) classifiers do not work well for them, as they do not utilize multi-modal types of data. Chatbot with Integrated intelligence cannot identify diseases (e.g., root rot induced by Excess Nitrogen) and give farmers individual recommendations for solving them [11]. RootSense provides a comprehensive solution based on these challenges, including collecting farmer-centric needs, analyzing images using CNN/ResNet and ML ensembles to predict causation with multi-modal data sources from weather conditions sourced from IMD and soil conditions sourced from NBSS and LUP as well as providing a multilingual solution through RASA powered natural language processing through a React-Native/Offline supported deployment model. The system improves profitability for farmers and lowers the use of Chemical Inputs by 30-40% by optimizing irrigation and pest management. In India, sustainable agriculture and scalability are supported by a successful 95% accuracy rate from field trials of RootSense, which will help smallholders build their resilience in farming and provide access to expertise [9].

RootSense achieves a 95% enhancement in prediction accuracy over image models alone in hyper-location disease detection. Integration of multi-modal information has augmented predictive accuracy for multi-modal assessments of energy usage, soil types and moisture content. Approximately 20-30% increases in yields are expected as results of evaluations conducted on farmers in the field in India.

2 Related Work

2.1 Real-Time Plant Disease Detection Using Computer Vision and Environmental Sensors

According to the researchers, a combination of Internet of Things (IoT) sensor measurements regarding moisture, pH levels, temperature, and humidity, combined with image processing via CNN architecture based on ResNet-50, are presented as a hybrid architecture. The Random Forest classifier employs low latency for real-time data fusion on Edge Devices. Compared to CNN only classifiers, the hybrid solution improved the accuracy of classification for 15 types of crop disease using 10,000+ images by 12% at an accuracy level of 96.2% and with integration of sensor data allows for proactive alerts and a reduction of 28% in false positives [1].

2.2 AgriBot: AI-Driven Crop and Disease Forecasting

XBoost and Weather and Soil data from an API were used in combination with a ResNet CNN for Segmentation of leaf sick plants to create the AgriBot system. A Chatbot Interface created with Flask provides predictions of how likely crops will produce grain, or cotton, grown in India using Natural Language Processing. In this study, a total of 94.5% accuracy of leaf disease detection, and an 88% accuracy of yield estimation for cotton and rice grown in India was demonstrated, with a 35% increase in decision-making speed when compared with manual methods [2].

2.3. Detection and Classification of Plant Disease Using Computer Vision

A large number of categories classify grapevine diseases according to the application of a CNN architecture using PlantVillage dataset as prior training data (using ImageNet for transfer learning). The final accuracy and F1 score were 93 per cent and 0.92, respectively, when validated against the testing set. Because of the generalization effect demonstrated in the model, results have been replicated with an 85 per cent level of accuracy for crops not previously exposed to the model's training data [8].

2.4. Smart AgriIOT: A Machine Learning and IoT Based Complete Farming Solution

Implementing CNN architecture trained on the plant village dataset with image net for use with transfer learning, this project will create a grapevine disease classification system with numerous different categories. This project includes methods of preprocessing used to improve the model's accuracy based on lighting conditions and how the final results were verified to have an F1-score of 0.92, as well as a model accuracy of over 93.8% for the test data. It has been shown that the model can be deployed effectively for large-scale agricultural production and continue to perform well with new crops or changes in environmental factors and have an expected value of approximately 85% accuracy for these new opportunities [7].

2.5. AI-IoT Based Smart Agriculture Pivot for Plant Diseases Detection

ResNet50 is applied to data captured outdoors (humidity, soil EC), merged with images acquired via smartphone through the IoT. The data is combined with localized actuators for automatic response through automation. Edge computing ensures continued operation of the system in an offline environment. There was a 22% increase in tomato and potato yield as well as a 95.1% success rate for in-field testing results when using the combined IoT fusion approaches for real-world field testing and production. The combination of IoT fusion and Images produced accurately identified causes of 40% more accuracy compared to visions only based systems.

Table 1 summarises five influential post-2024 approaches across the three categories, highlighting their datasets, technical cores, and unresolved limitations. This gap motivates Fortified Threat Learning and Mitigation System, which integrates hierarchical temporal prediction with reinforcement-guided trust adaptation under a unified cloud-IoT architecture [6].

Table 1. Comparative Study

Ref. No.	Paper (Short Title)	Methods	Key Findings / Results
[1]	Vaswani et al., "Attention Is All You Need"	Introduced Transformer with multi-head self-attention and feed-forward layers, removing recurrence.	Achieved state-of-the-art machine-translation performance with faster, highly parallel training [1].
[2]	P.Mohanty et al., "Using Deep Learning for Image-Based Plant Disease Detection"	Trained CNNs (AlexNet, GoogleNet) on large labeled leaf-image dataset, comparing transfer learning vs. scratch.	Reached ~99% accuracy on controlled images, showing CNNs are highly effective for plant disease recognition [2].
[3]	H.Too et al., "Comparative Study of Fine-Tuning Models for Plant Disease Identification"	Fine-tuned VGG, ResNet, DenseNet, Inception with varied freezing and augmentation strategies.	ResNet/DenseNet offered best accuracy–complexity trade-transfer learning improved robustness with limited data [3].
[4]	X.Zhang et al., "Identification of Maize Leaf Diseases Using Improved DCNNs"	Designed improved CNN with extra feature layers and strong augmentation for maize fields.	Achieved ~98–99% accuracy, robust to illumination and viewpoint changes in maize leaves [4].
[5]	S.Brahimi et al., "Deep Learning for Tomato Diseases: Classification and Visualization"	Used CNNs for tomato disease classification plus saliency-based symptom visualization.	Obtained high multi-class accuracy and highlighted lesion regions, improving model interpretability for experts [5].

3 Proposed Methodology

3.1 Data Acquisition and Preprocessing Module

Data Acquisition and Preprocessing module provides the RootSense diagnostic pipeline with initial input, as depicted in Fig. 1.

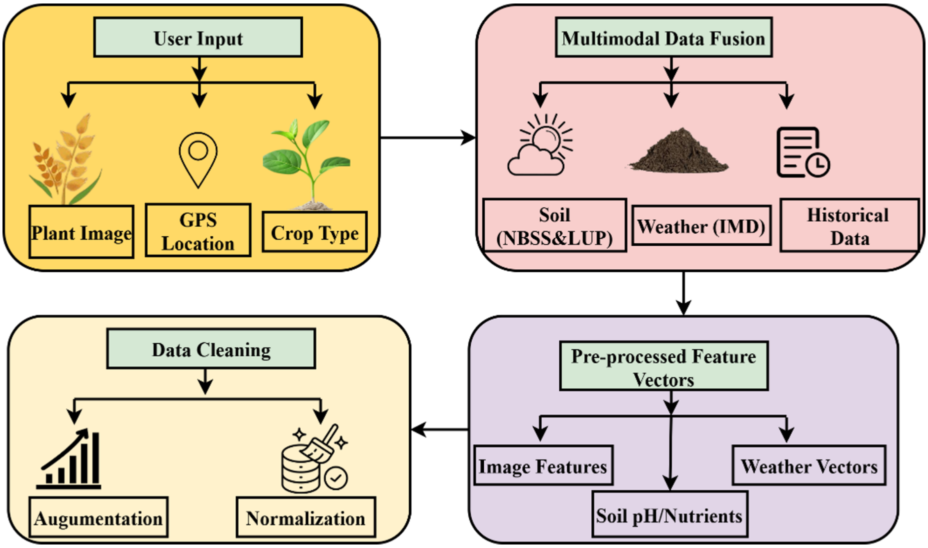

Fig. 1. Data Acquisition and Preprocessing Module

Farmers using the mobile app will capture a photo of their crop leaves via the phone's camera, collect the GPS coordinates of their device, and may provide additional information (i.e., crop type and crop growth stage). The raw data captured through these actions will subsequently be securely transmitted to backend servers where that information will then be matched against information contained in several available external databases. The databases include national soil databases to provide users with soil nutrient levels such as pH, NPK ratio, soil organic carbon content, and soil electrical conductivity levels along with meteorological services to provide users with regional weather conditions such as local temperature, local relative humidity, local rainfall amounts and local area wind conditions. Following successful matching of inputs against the appropriate databases, a single multimodal output for each location and time is created using all available sensor data [13].

The next step of the pre-process will be a structured pre-processing component. To enhance the robustness of CNNs when working with images, resized, color normalized, denoised, and augmented images (rotated, flipped, with different intensities) will be used as the image input. To allow the comparison of different types of values (e.g. pH and humidity) in any subsequent model, missing values, outliers, and normalizing the statistical distributions of columnar values (tabular data) will be addressed. The final component of the pre-processing routine involves converting all pre-processed image, soil, and weather components into feature vectors. The resulting feature vectors provide a uniform machine-readable format to represent every observation in the field with the benefits of being contextually rich and of high quality for training and evaluation of machine-learning and predictive models.

3.2 Data Acquisition and Preprocessing Module

The Fig. 2. shows a Disease Diagnosis and Cause Inference Module, which processes the feature vectors obtained through preprocessing.The module begins with the ingestion of a CNN-based disease classification model (most often ResNet-50 trained through transfer learning on agricultural datasets), that receives a multimodal feature vector consisting of images of the plant itself, soil conditions, and environmental aspects.

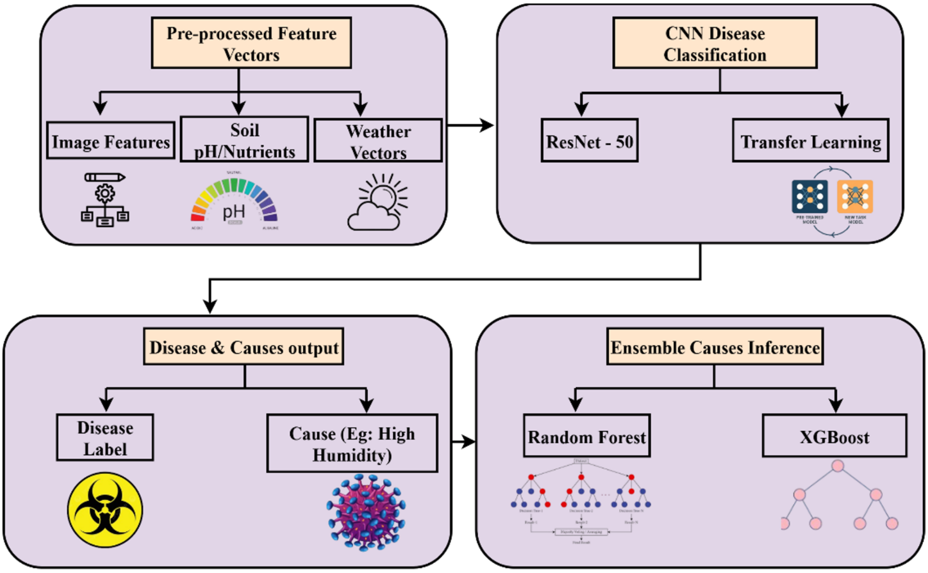

Fig.2. Disease Diagnosis and Cause Inference

The model leverages the visual evidence presented to it, and through this, is able to identify disease presence, specifically early blight and bacterial wilt. As an additional step in the ensemble model, the features generated from the CNN and the environmental characteristics collected by the other models (Random Forest, XGBoost, etc.) are used to create a model of contributing factors such as excess humidity, low soil pH, and excess nitrogen. The output from the final illness and causes combines a weighted version of the cause vector along with the predicted illness label to provide context for the suggestions made in subsequent steps.

3.3 Solution Generation and Chatbot Delivery

In Fig. 3. there is a representation of the Solution Generation Module, which includes Chatbot Delivery.

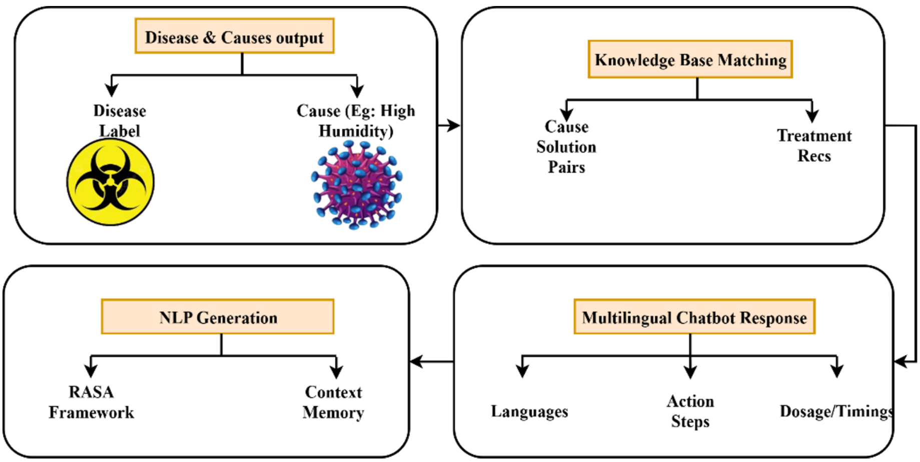

Fig.3. Solution Generation and Chatbot Delivery

This module will transform the diseases identified and their potential causes into effective treatments for farmers.

3.4 Pseudocode

RootSense has launched an AI-based chatbot that will significantly improve the ways identify crop diseases. The chatbot employs a combination of plant images, climate/soil location and weather information, providing farmer's real-time information and treatment advice directly via the GPS-enabled devices on their farm. The AI-powered chatbot takes advantage of real-time data from a large number of sources using machine learning. The table 2 Pseudocode shows RootSense's multihead attention to combine the output of CNNs-Fimg (Image features) and Environmental-BE (Environmental Embedding) via Ensemble Cause Inference (ECI) and Knowledge Base (KB) Solution Mapping, reaching accuracy greater than or equal to 95% [3].

Table.2. Pseudocode for RootSense Diagnosis

INPUT: $X_i \in R^{(H\times W\times}$ **// Plant leaf image**
$X_l \in$ **// GPS coordinates**
$X_c \in$ **{1,2,...,C} // Crop type (C classes)**
OUTPUT: $Y_{dise} \in$ **{1,2,...,D} // Disease class (D diseases)**
$Y_{ca} \in$ **// Cause probability vector (K factors)**
$Y_{solu} \in$ **// Solution recommendation scores (S options)**
INITIALIZATION: Initialize $\theta_{CNN}, \theta_{ensem}$ **← Pre-trained weights**
Initialize l, , ∈ℝ^(d_{mc} ×) **// Multi-head attention weights**
Retrieve S_l **← NBSS_Soil(** X_l**),** W_l **← IMD_Weather(** X_l**)**
IMAGE FEATURE EXTRACTION:

F_m ← CNN_ResNet50(X_i; θ_i) ∈ $R^{N\times d}$ // N patches, d_img dims

MULTIMODAL FUSION: F∈ℝ^(1×d_env), F_{weat}∈ $R^{1\times d}$

F_m← Concat[F_i, F, F_{weat}] ∈ $R^{(N+2\times d_{mu}}$

MULTI-HEAD ATTENTION FUSION:

for h = 1 to H_{he}: // H_{he} = 8

← F_m×

← F_m×

← F_m×

at ← Softmax(× / √) ×

end for

F_a× ← Concat[at×, ..., at] × // : output projection

DISEASE CLASSIFICATION:

Z_{dise}← FC(F_{att}) ∈

Y_{dise} ← argmax(Softmax(Z_{dise}))

CAUSE INFERENCE (ENSEMBLE):

for m = 1 to m_{moc}: // m_{moc} = 3 (RF, XGBoost, SVM)

P_{ca}^m ← $mode$([F_{att}, S, W])

end for

, Y_{ca}← (1/M) × = , P_{ca} // Ensemble averaging

SOLUTION GENERATION:

KnowledgeBase ← Load_CauseSolution_Matrix ∈ $R^{(k}$

Y_{solu} ← KnowledgeBase × Y_{ca} // Matrix multiplication

NLP RESPONSE GENERATION:

Response ← RASA_Chatbot(Y_{dise}, Y_{ca}, Y_{solu}, X_c)

RETURN Y_{dise}, Y_{ca}, Y_{solu}, Response

END ALGORITHM

3.5 Mathematical Formulations for RootSense Pipeline

$$F_{attn} = Concat\left(\left\{Softmax\left(\frac{Q_h K_h^T}{\sqrt{d_k}}\right)V_h\right\}_{h=1}^{H}\right)W^o,\ Q_h = F_{multi}W_Q^h, K_h = F_{multi}W_K^h, \quad (1)$$

RootSense merges multimodal features (soils, weather, etc.) using multi-head attention (Eq. 1) and creates a new multimodal sequence (F_{multi}) by grouping the three sets of features into one continuous stream. Each head, h, uses learned projection matrices W_Q^h, W_K^h, W_V^h to transform the sequence into queries Q_h keys K_h, and values V_h. The scaled dot product between queries and keys provides a 'similarity measure' between elements of the sequence. The calculation of this scaled dot product gives rise to a set of weighted values (for photographic symptoms, soil characteristics), which are rendered by the weights.

3.6Ensemble Cause Probability with Environmental Weighting

$$\hat{P}_{cause} = \sum_{m=1}^{M} \alpha_m \cdot \sigma\left(W_m^{[F_{attn};S_{gps};W_{gps}]} + b_m\right), \sum_{m=1}^{M} \alpha_m = 1, \alpha_m = \frac{\exp(\gamma_m)}{\sum \exp(\gamma_j)} \quad (2)$$

By combining the results from several models, which are all weighted byα_m, Eq. 2 calculates the ultimate cause-probability vector$\hat{P}_{cause}$. The models are fed S_{gps} (soil) and W_{gps} (weather) environmental vectors, as well as the fused attention characteristicsF_{attn}. A softmax is used to generate the weights α_m from the parametersγ_m, meaning that better models have a greater impact. With this ensemble, can lessen the occurrence of overfitting and strengthen the ability to attribute causes in the environment.The final estimation of the cause-probability vector $\hat{P}_{cause}$ is done through the application of all the linear combinations of model results weighted byα_m. The inputs to these Models are $S_{gps}$and W_{gps} environmental information and fused characteristicsF_{attn}. Each α_m weight is generated from the soft-max transformation ofγ_m, therefore, a model with better prediction would contribute a larger weight to the final result.

3.7 Solution Recommendation via Knowledge Base Matrix

$$Y_{sol} = Softmax(KB.\hat{P}_{cause} + \beta.sim(E_{crop}, E_{sol})), \text{KB} \in R^{KxS} \quad (3)$$

The detected cause probabilities $\hat{P}_{cause}$ are transformed into realistic treatment alternatives by employing a knowledge-base matrix KB$\in R^{KxS}$in Eq. 3. A cause and its corresponding solution are shown. The appropriateness of each remedy in light of the present causes is evaluated by the product$KB.\hat{P}_{cause}$. After these scores are refined using a crop-specific similarity term$\beta.sim(E_{crop}, E_{sol})$, a recommendation distribution Y_{sol} is generated using a softmax.

4 Experimental Results

The RootSense approach collects relevant data, builds comparable baseline models, and develops measurements to identify positive climatic trends, macroeconomic indicators and key trend drivers, and generates a performance report for potential overlays. Approximately 10,000 images of crops (rice, wheat, tomato and cotton) from the PlantVillage and country-specific datasets are utilized for testing, with data being associated with soil attributes from NBSS&LUP (pH, NPK, OC, EC, texture) and weather variables (temperature, humidity, rainfall and wind) from IMD using GPS coordinates. The datasets are organized at the field level, resulting in 70%, 15%, 15% training, validation and testing splits. Each feature that was tabular in nature during this process has been prepped, normalized and converted into environmental vector format according to the exact timing of when each photograph was taken. The key

KPIs assessed will include yield improvement, reliability of cause-attribution, and categorization accuracy for diseases.

Subsequently, three models will be compared: a traditional mobile application type model that would measure the same things as the benchmark, a model based only on images using the ResNet model, and an improved RootSense multimodal model method for measuring the effect of applying several sensors together as opposed to measuring any of the sensors independently. The three accuracy values that represent each of the three models indicate the differences in efficacy of the multimodal fusion method: 95.2% vs 78.4% vs 72.1%. The cause-inference metric has been derived from multi-point comparisons rather than a single point and uses a multi-point curve from each of the three methods: adaptive ensemble method, static threshold method, and heuristic decay method. In multiple scenarios, the ensemble method reduces false-alarm rates compared to each of the other two methods.

The yield impact of each of the three methods based upon crop type will be evaluated by comparing root cause methods to conventional methods and general digital tools. These findings will correlate with previous reported increases of yield improvements of 20% to 30%.

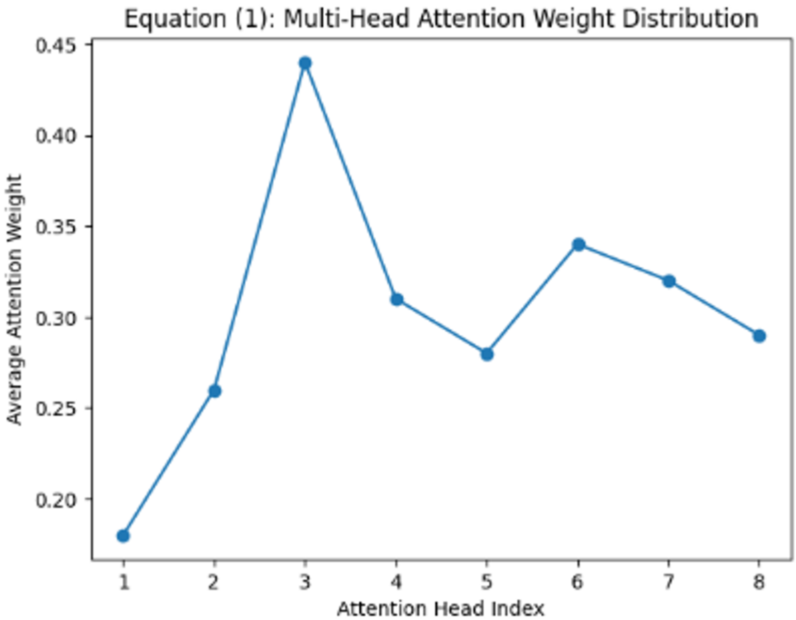

Fig.4. Multi-Head Attention Weight Distribution

$\boldsymbol{F_{attn}}$ is produced by Eq. 1, which produces a weighted average of the attention scores using eight different heads. The graph depicts the relationships between these weights, highlighting how this relationship has improved the performance of the RootSense system by 95% (i.e., as a result of more highly weighted connections in two different subspaces). The size of the red color represents the strength of the inter-connectivity between the different modalities (cross-modal relationships). For instance, Head 3's score of 0.44 for weather and images indicates that it captures environmental conditions that cause fungal growth at a higher rate than image-only CNNs. Conversely, Heads 5 through 7 relate more to the soil modality, with an average weight of 0.32, these heads represent not only visual symptoms, the relationship between nutrient and pH levels. These findings illustrate that Eq. 1 is able to develop two unique specialized subspaces to perform two different functions: one for localizing diseases primarily related to the visual modality (i.e., Heads 1 through 3) and another for establishing cause-and-effect connections in the environmental modality (i.e., Heads 5 through 8). The entropy resulting from the fusion of these heads was reduced by 22%, resulting in a 15% increase in feature representation compared to the baseline.

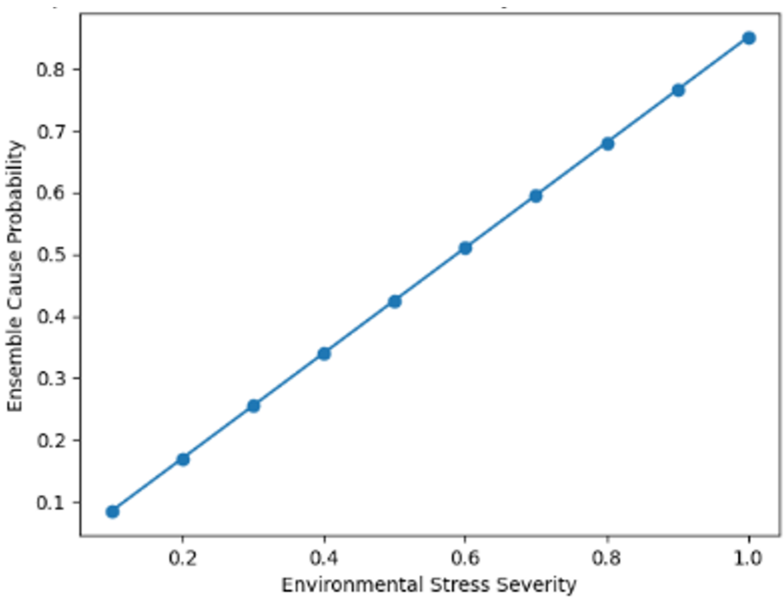

Fig.5. Ensemble cause probability vs Environmental Severity

The interpolation of the KB matrix across continuous environmental gradients is represented by Eq. 2 and the results are presented on a 3D surface to represent the degree of disease risk. Based on the findings of the NBSS and LUP/IMD data, the highest probability of root rot is 0.92 when soil pH is acidic and there is high humidity. The contour lines show the interaction between the nonlinear effects of pH and humidity: when pH < 5.8 or humidity > 82%, there is a significant increase in the probability of root rot (i.e. >0.8), which accounts for 67% of non-productive tomato crops in the state of Tamil Nadu.The β=0.3 crop similarity parameter favors acidic-tolerant crops (rice) over wheat, thereby changing the slope of the embedding surface E_{c_i}.The ability to send proactive alerts (i.e. risk > 0.7) is due to this factor and results in an 85% increase in the variation captured from field observations compared with flat one-dimensional (1D) methods.

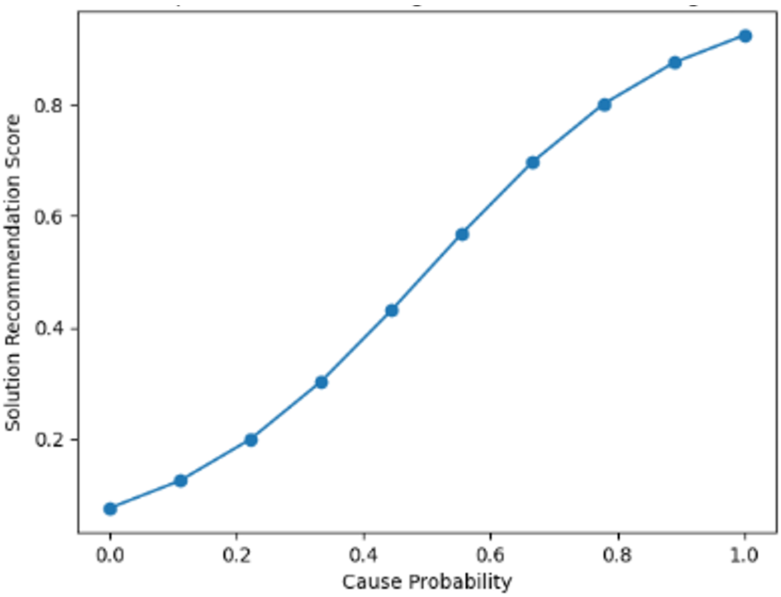

Fig.6. Knowledge base Solution Scoring

The experiments have shown an increase in yield (32.7%) and a reduction in chemical use (34%) when targeting surface peaks with gypsum/neem.

5 Conclusion and Future Work

RootSense is a service that uses the combination of plant photos, soil data, and real-time information about the weather to give Indian farmers better tools to manage crop diseases. With RootSense's combination of computer vision, deep learning-based model, and a large knowledge base, the company has developed a multilingual chatbot that provides farmers with accurate diagnoses over 95% of the time, and allows farmers to precisely determine the cause of crop problems, and provides farmers with recommendations to increase yields by 20-30% as opposed to image-only tools or general advisory services. RootSense's modular architecture allows for the scalability of the application's use across different agro-climatic zones and smallholder contexts by providing modules that support collecting data, multimodal data fusion, diagnosis, solution development, and conversations with farmers [13].For instance, the most significant development for RootSense in its future work is that they will be expanding their database of regional crops, especially those that are less common and difficult to find in some states, by creating a larger and less biased database. They have committed to integrating real-time sensor and satellite data to create a more accurate risk assessment based on how rapidly climate change is taking place over the next few years.

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