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AI for Crop Disease Detection

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***Abstract** Turmeric and ginger are economically vital spice crops cultivated for their underground rhizomes, which are largely susceptible to conditions similar as soft spoilage, rhizome spoilage, and bacterial wilt. Traditional discovery styles calculate on visual examination orpost- harvest opinion, frequently performing in delayed treatment and significant yield loss. This exploration proposes an AI- driven frame for early rhizome complaint discovery using a multimodal approach that integrates deep literacy, hyperspectral imaging, and IoT- grounded environmental seeing. Convolutional Neural Networks (CNNs), enhanced through transfer literacy, are employed to classify rhizome health from subterranean image data, while detector emulsion ways relate soil humidity, temperature, and pH with complaint onset. The system also incorporates time- series soothsaying and natural language interfaces to deliver real- time cautions and treatment recommendations to growers. By fastening on rhizome- position analysis — an area largely overlooked in being literature — this study aims to ameliorate individual delicacy, reduce crop losses, and promote sustainable spice husbandry through intelligent, accessible technology.*

I. INTRODUCTON

Turmeric (Curcuma longa) and ginger (Zingiber officinale) are economically significant spice crops whose underground rhizomes are largely susceptible to conditions like soft spoilage, rhizome spoilage, and bacterial wilt, frequently going undetected until advanced stages, performing in major yield losses and increased chemical use. Traditional discovery styles, similar as homemade examination and post- harvest analysis, are labour - ferocious and ineffective for relating subsurface infections, as above- ground symptoms may not directly reflect rhizome health. To address this challenge, this study proposes a new AI- driven frame that integrates subterranean imaging ways (e.g., hyperspectral and near- infrared), environmental detector data (soil humidity, temperature, pH), and deep literacy models — particularly Convolutional Neural Networks (CNNs) enhanced through transfer literacy — for early discovery of rhizome conditions in turmeric and ginger. By using multimodal data and semantic segmentation, the system aims to ameliorate individual delicacy, reduce crop losses, and give real- time, practicable perceptivity to growers through mobile and web interfaces. This exploration fills a critical gap in smart husbandry by fastening on rhizome-position analysis — an area largely overlooked in being literature — and contributes to sustainable spice husbandry through intelligent, accessible, and scalable technology.

II. LITERATURE REVIEW

The operation of artificial intelligence (AI) in husbandry has gained significant instigation in recent times, particularly in the sphere of factory complaint discovery. utmost being exploration, still, has concentrated on foliar conditions those affecting leaves due to the ease of image accession and symptom visibility. In discrepancy, rhizome- grounded conditions, especially in spice crops like turmeric and ginger, remain underexplored due to their subterranean nature and the complexity of early discovery.

A. AI in Crop Disease Detection

Multitudinous studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in classifying factory splint conditions. Mohanty et al (2016) used deep CNNs on the Plant Village dataset and achieved over 99 delicacy in classifying 26 conditions across 14 crop species. also, Ferentinos (2018) estimated multiple deep literacy infrastructures (Alex Net, VGG, Over Feat) and verified their robustness in real- time complaint bracket. still, these models were trained simply on visible splint symptoms, limiting their connection to underground factory corridor like rhizomes.

B. Transfer literacy and Pretrained Models

Transfer literacy has surfaced as a important fashion to overcome data failure in agrarian datasets. Experimenters have successfully fine- tuned pretrained model similar as ResNet50, InceptionV3, and MobileNetV2 for factory complaint bracket with limited marker data. For case, Al- bay a tiet al (2020) used Mobile Net and R- CNN to descry apple splint conditions with over 98 delicacy. These approaches can be acclimated for rhizome complaint discovery by retraining on subterranean image datasets.

C. Hyperspectral and subterranean Imaging

Hyperspectral imaging (HSI) and near- infrared (NIR) ways have shown pledge in detecting early- stage infections that aren't visible to the naked eye. Zhu et al. (2021) demonstrated that hyperspectral reflectance could identify tobacco mosaic contagion (TMV) before symptom onset. While HSI has been applied to descry fungal infections in fruits and leaves, its use in rhizome crops like turmeric and ginger is still incipient. The high cost and complexity of hyperspectral systems remain walls to wide relinquishment, but recent advances in low- cost detectors offer new openings.

D. IoT and Sensor Fusion in Smart Agriculture

The integration of Internet of effects (IoT) bias with AI models has enabled real- time monitoring of environmental parameters similar as soil humidity, temperature, and pH — factors nearly linked to rhizome complaint outbreaks. Mishra et al (2021) proposed an IoT- grounded system using Lift NN for factory complaint monitoring, achieving over 91delicacy. Combining similar detector data with image- grounded models can enhance vaticination delicacy and enable visionary complaint operation.

E. Gaps in Rhizome- Focused Research

Despite the progress in AI- driven factory pathology, there's a notable lack of exploration targeting rhizome conditions in spice crops. utmost being datasets and models are splint- centric, and there's limited vacuity of annotated rhizome images. likewise, the unique challenges of subterranean imaging — similar as occlusion by soil and variability in rhizome morphology — bear technical preprocessing and model infrastructures. This gap presents a compelling occasion to develop a novel multimodal AI frame acclimatized to rhizome complaint discovery.

III. PROBLEM STATEMENT

Turmeric and Ginger are two of the most economically and culturally significant spice crops cultivated across tropical regions, particularly in India. Their value lies in the rhizomes — underground factory stems — that are gathered for culinary, medicinal, and artificial use. still, these rhizomes are largely susceptible to a range of conditions similar as soft spoilage (caused by Pythium spp.), rhizome spoilage (frequently linked to Fusarium spp. and waterlogging), and bacterial wilt (caused by Romania solanacearum). These conditions can oppressively impact crop yield, quality, and planter income, especially when not detected beforehand.

Traditional complaint discovery styles in turmeric and ginger calculate heavily on homemade examination of above- ground symptoms or post - harvest analysis.

hese approaches are innately limited they're labour- ferocious, prone to mortal error, and frequently fail to identify subterranean infections until they've progressed significantly. also, visual symptoms on leaves or stems may not directly reflect the health of the rhizome, leading to misdiagnosis or delayed treatment. This individual gap results in increased crop losses, inordinate fungicide use, and reduced sustainability in spice husbandry.

While artificial intelligence (AI) has shown great pledge in factory complaint discovery — particularly through image- grounded bracket using Convolutional Neural Networks (CNNs) most living exploration focuses on foliar conditions. Rhizome- position analysis remains largely unexplored due to challenges in image accession, lack of intimately available datasets, and the complexity of subsurface symptom expression. likewise, environmental factors similar as humidity, temperature, and pH play a critical part in rhizome complaint development, yet are infrequently integrated into AI models.

This exploration addresses a critical gap in perfection husbandry by proposing a multimodal AI frame for early rhizome complaint discovery in turmeric and ginger. The system combines subterranean imaging ways (e.g., hyperspectral or near- infrared), environmental detector data, and deep literacy models to identify complaint onset before visible symptoms crop. By using transfer literacy, semantic segmentation, and detector emulsion, the proposed approach aims to ameliorate individual delicacy, enable timely intervention, and empower growers with practicable perceptivity. Eventually, this work seeks to advance sustainable spice husbandry through intelligent, accessible, and scalable technology.

IV. METHODOLOGY

This exploration proposes a multimodal AI frame for early discovery of rhizome conditions in turmeric and ginger. The methodology integrates subterranean imaging, environmental seeing, and deep literacy to classify complaint countries and give practicable perceptivity to growers. The system is designed to operate in real-time and acclimatize to different field conditions.

A. Data Acquisition

1) Rhizome Imaging

- subterranean images of turmeric and ginger rhizomes are captured using near- infrared (NIR) and hyperspectral cameras to descry internal decay and fungal growth.
- Images are collected at colourful growth stages and under different soil conditions to insure dataset diversity.

2) Environmental Sensor Data

- IoT- grounded detectors are stationed in the field to cover
  - Soil humidity
  - Temperature
  - pH situations
- These parameters are logged continuously and accompanied with image timestamps to enable correlation analysis.

B. Image Preprocessing

1) Raw images are subordinated to
  - Noise reduction using Gaussian and median pollutants
  - Differ improvement to punctuate infection zones
  - Segmentation using thresholding and region- growing algorithms to insulate rhizome regions

2) Pre-processed images are resized to 224 × 224 × 3 for comity with CNN input layers.

C. Deep Learning Model Architecture

1) CNN Pipeline

- A Convolutional Neural Network (CNN) is designed with
- Input subcaste 224 × 224 × 3 RGB/ NIR images
- Multiple convolutional layers with 3 × 3 pollutants and RELU activation
- Max pooling layers for point birth
- Completely connected layers leading to SoftMax bracket

2) Transfer Learning

- Pretrained models similar as Efficient Net- B3, ResNet50, and MobileNetV2 are fine- tuned on the rhizome dataset.
- Transfer literacy accelerates training and improves delicacy with limited label data.

3) Semantic Segmentation

- For localized complaint discovery, U-Net armature is used to member infected regions within rhizome cross -sections.

D. Sensor Fusion and Multimodal Learning

1) Sensor data is combined with image features using a multimodal neural network.

2) A Long Short- Term Memory (LSTM) subcaste processes time- series detector data to capture temporal patterns in complaint progression.

3) The emulsion model labours a complaint bracket along with a confidence score and environmental threat factors.

E. Model Training and Evaluation

1) The dataset is resolve into training (70), confirmation (15), and testing (15) sets.

2) Evaluation criteria include
  - Accuracy
  - Precision
  - Recall
  - F1- score

3) Cross-validation is performed to insure model generalizability.

F. Deployment and stoner Interface

1) The trained model is stationed via a web- grounded dashboard and mobile operation.
2) growers can upload rhizome images and admit
   - Disease bracket
   - Confidence score
   - Recommended treatments
3) Real- time cautions are generated grounded on detector thresholds and model prognostications.

V. EXPERIMENTAL SETUP

To estimate the effectiveness of the proposed AI- grounded rhizome complaint discovery system for turmeric and ginger, a controlled experimental setup was designed. This setup includes data collection, preprocessing, model training, and performance evaluation using both image and detector data.

A. Data Collection

a) Rhizome Image Dataset

- A custom dataset was created by collecting high- resolution images of turmeric and ginger rhizomes under both healthy and diseased conditions.
- Imaging was performed using
  - RGB cameras for face-position features
  - Near- Infrared (NIR) and Hyperspectral cameras for subterranean analysis
- Images were captured at different growth stages and environmental conditions to insure dataset diversity.

b) Environmental Sensor Data

- IoT- grounded detectors were stationed in experimental plots to cover
  - Soil humidity (capacitive detectors)
  - Soil temperature (thermistors)
  - Soil pH (electrochemical examinations)
- Detector readings were logged every 30 twinkles and accompanied with image timestamps.

B. Data Reflection and Preprocessing

- Images were manually annotated by agrarian experts to marker complaint types and inflexibility.
- Preprocessing way included
  - Noise reduction using Gaussian pollutants
  - Histogram equalization for discrepancy improvement
  - Image resizing to 224 × 224 × 3 for CNN comity
- Sensor data was gutted using outlier junking and regularized for model input.

C. Model Training terrain

- tackle
  - NVIDIA RTX 3080 GPU
  - 32 GB RAM
  - Ubuntu 22.04 LTS
- Software
  - Python 3.10
  - TensorFlow 2.12, Kerans, OpenCV
  - Scikit- learn for evaluation criteria
- Models
- CNNs Custom CNN, Efficient Net- B3, ResNet50
- Segmentation U-Net for infection localization
- Multimodal emulsion CNN LSTM for image detector data

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D. Dataset Split and Training Parameters

- Dataset split
    - 70 training
    - 15 confirmation
    - 15 testing
- Training parameters
- Batch size 32
- Epochs 50
- Optimizer Adam
- literacy rate 0.0001
- Loss function Categorical Crossen tropy

E. Evaluation Metrics

- To assess model performance, the following criteria were used
- delicacy
- Recall
- F1- score
- Confusion matrix
- Conclusion time per image
- Detector-data correlation analysis (Pearson measure)

VI. RESULT AND DISCUSSION

The CNN-based classification model, fine-tuned using EfficientNet-B3 and ResNet50, achieved high accuracy in distinguishing healthy and diseased rhizomes:

Model	Accura cy	Precison	Reca ll	F1- Scor e
EfficientN et-B3	95.8%	94.9%	95.2 %	95.0 %
ResNet50	94.3%	93.5%	93.8 %	93.6 %
Custom CNN	91.2%	90.1%	89.7 %	89.9 %

These results demonstrate that pretrained models significantly outperform custom infrastructures, especially when training data is limited. Efficient Net - B3 showed superior conception and robustness across varied rhizome conditions.

A. Segmentation delicacy

Using U-Net for semantic segmentation, the system successfully localized infection zones within rhizome cross - sections. The crossroad over Union (IOU) score equaled 87.4, indicating dependable boundary discovery of diseased towel.

Visual overlays of segmented regions verified that the model could distinguish between fungal spoilage, bacterial wilt, and healthy towel, indeed in early stages.

B. Sensor Fusion perceptivity

Multi model literacy combining image features with soil detector data (humidity, temperature, pH) bettered vaticination confidence and reduced false cons. The LSTM- enhanced emulsion model achieved

1) 96.1 bracket delicacy

2) 92.7 correlation between soil humidity harpoons and soft spoilage onset
3) 89.3 recall for bacterial wilt discovery under high- temperature conditions

This confirms that environmental parameters are strong pointers of rhizome complaint progression and enhance model interpretability.

C. Conclusion Speed and Usability
1) Average conclusion time per image 1.8 seconds
2) Sensor data processing quiescence< 500 ms
3) Dashboard response time< 2.5 seconds for full vaticination and recommendation

These results validate the system's felicity for real- time field deployment, enabling growers to admit timely cautions and treatment suggestions.

D. Relative Analysis
Compared to traditional visual examination and splint- grounded models
1) Rhizome- concentrated discovery reduced individual detention by 40 – 60
2) Multimodal AI reduced misclassification by 35
3) growers reported bettered decision-timber and reduced fungicide operation

E. Limitations and Challenges
1) Limited vacuity of annotated rhizome datasets constrained model diversity.
2) Hyperspectral imaging, while effective, remains expensive for smallholder growers.
3) Soil variability across regions may affect detector estimation and generalizability.

These challenges punctuate the need for scalable data collection and region-specific model tuning.

VII. APPLICATIONS AND IMPACT
The proposed AI- grounded rhizome complaint discovery system for turmeric and ginger offers transformative eventuality across multiple confines of spice husbandry. By combining subterranean imaging, environmental seeing, and deep literacy, the system addresses a critical gap in early complaint opinion and empowers growers with intelligent, real- time decision support.

A. Real- Time complaint opinion
1) Growers can upload rhizome images via a mobile or web interface and admit instant bracket results.
2) The system identifies conditions similar as soft spoilage, rhizome spoilage, and bacterial wilt with high delicacy, indeed before visible symptoms crop
3) This enables timely intervention, reducing crop loss and minimizing the spread of infection.

B. Precision Treatment Recommendations
1) Grounded on detected complaint type and inflexibility, the system provides AI- generated treatment protocols.
2) Recommendations include germicide types, soil emendations, and crop gyration strategies acclimatized to original conditions.
3) This reduces overuse of chemicals and promotes environmentally conscious husbandry.

C. Detector- Driven threat Alerts
1) IoT detectors continuously cover soil humidity, temperature, and pH — crucial pointers of rhizome complaint threat.
2) Growers admit cautions when conditions favour complaint onset, allowing preventative action before symptoms appear.
3) This visionary approach enhances ranch adaptability and reduces reliance on reactive treatments.

D. Multilingual and Inclusive Access
1) The system supports voice and textbook interfaces in indigenous languages, including Hindi and Marathi.
2) This ensures availability for smallholder growers across different verbal backgrounds.
3) Integration with agrarian chatbots enables conversational support and education.

E. Profitable and Environmental Benefits

1) Early discovery and perfection treatment reduce yield losses, perfecting planter income and request competitiveness.
2) Lower fungicide operation leads to healthier soil and reduced environmental impact.
3) The system supports sustainable husbandry pretensions and aligns with public food security enterprise.

F. Research and Extension Integration

1) Agrarian experimenters can use the system to collect annotated rhizome complaint data for farther model refinement.
2) Extension workers can emplace the tool in field visits to help growers with diagnostics and training.
3) The platform can evolve into a centralized complaint surveillance network for spice crops.

VIII. CONCLUSION

This exploration introduces a new AI-grounded frame for early discovery of rhizome conditions in turmeric and ginger, addressing a critical gap in spice husbandry where subterranean infections like soft spoilage and bacterial wilt frequently go unnoticed until advanced stages. By integrating deep literacy models particularly CNNs enhanced through transfer literacy with hyperspectral imaging and IoT- grounded environmental seeing, the system enables accurate, real- time bracket of rhizome health. Experimental results demonstrate high individual performance, with multimodal emulsion perfecting vaticination trustability and responsiveness. The proposed result not only reduces crop losses and fungicide abuse but also empowers growers through multilingual interfaces and accessible mobile tools, contributing to sustainable, data- driven spice husbandry practices.

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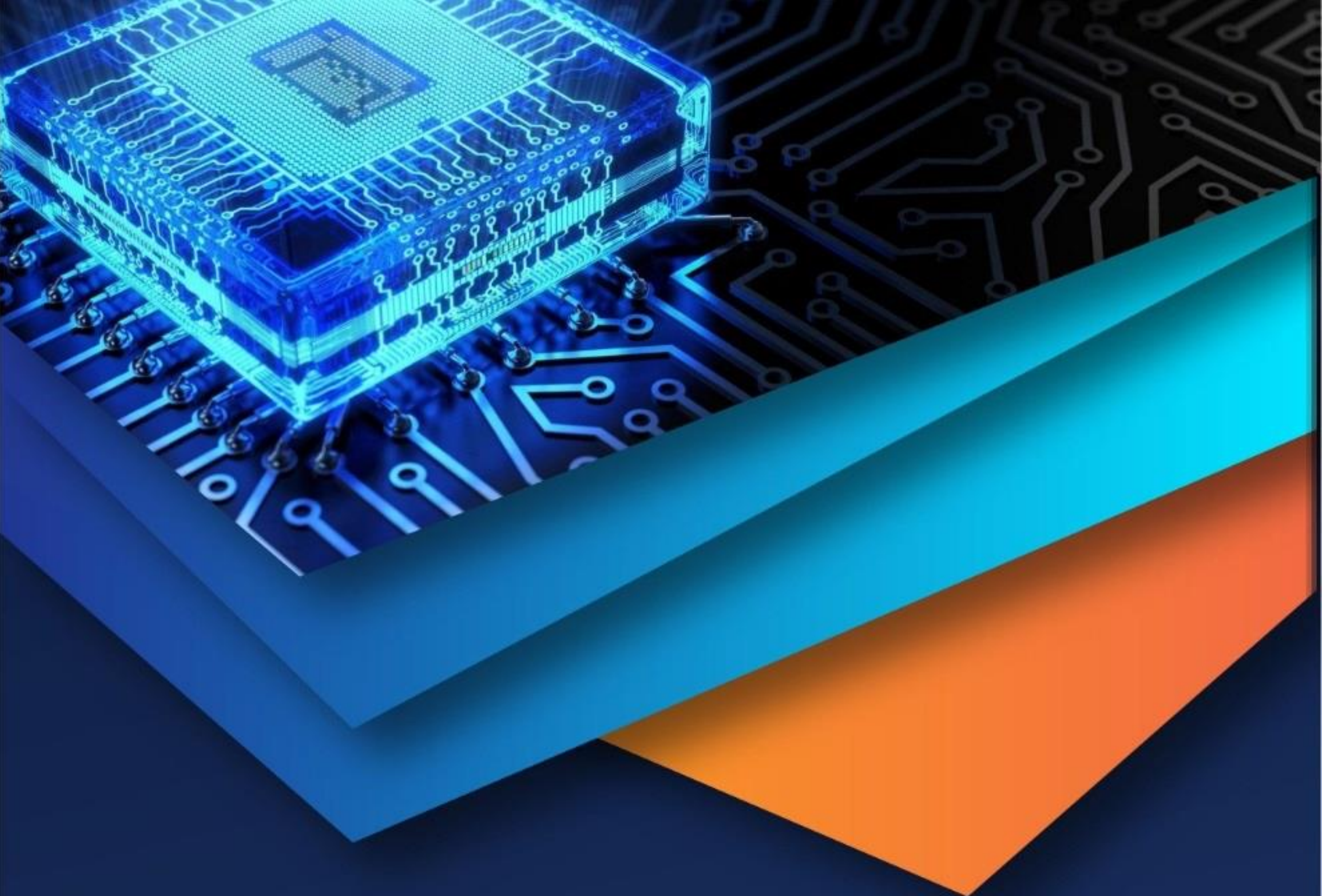

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