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AgroVision- Platform Independent Crop Analysis Using Deep Learning Techniques

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Abstract: Despite numerous efforts to incorporate emerging innovations into the agricultural domain for increasing crop yield and actively managing the state of the fields, it remains difficult for the industry to implement cutting-edge technologies in practice. This paper proposes AgroVision – a web-based intelligent multimodal system for comprehensive analysis of crops around the world. Designed using a three-layer scalable architecture, the system includes four modules – CNN-based growth stages and plant diseases recognition, AI Chatbot with LLM capabilities and RAG support, as well as the video analysis tool for detecting plant density and weeds. The key technology behind the core image analysis functionality of AgroVision is represented by the efficient Vision Mamba (ViM) architecture, which allows for analysing multiple tasks simultaneously using only one image uploaded by the user. Based on the extensive dataset called "New Plant Diseases Dataset" containing over 87 thousand images divided into 38 classes, the ViM model demonstrates exceptional results achieving weighted average F1-Score of 97.1%. Considering that the inference latency of the model does not exceed 25-40 milliseconds, the system can be deployed at the edge, providing an easy-to-use solution for farmers.
Keywords: Artificial Intelligence, Machine Learning, Agriculture, Multimodal System, Web Based Technology

I. INTRODUCTION

In addition to being one of the oldest traditional knowledge systems, farming and agriculture have been stagnant in adopting the modern solutions in the fields. Thereby farming is still a physically intensive and mentally draining activity. But still new tools can be used to boost crop production and manage finances more sensibly (1). However, there is frequently a gap between cutting-edge technologies and the typical farmer on the ground, who seeks useful, user-friendly solutions for everyday problems. Every day in the field, farmers and growers must make choices that could have an impact on an entire crop. They must exercise when they come across a field. Is this the real crop, or is it just weed.? Is it too early or a little late to add pesticides, or is the crop at the right stage of growth? (2) These assessments are frequently based on experience, and occasionally they are based solely on

speculation. A poor guess can result in overspending on the incorrect pesticide or missing the opportunity to apply nutrients, both of which have a negative financial impact on yields. Although mobile apps and digital tools have been created for agriculture, many of them present unique difficulties. Some require users to download and install complicated software, which isn't always easy to use. Additionally, a lot of tools don't take into consideration the particular weeds or crop varieties that are specific to our local fields because they are trained on global datasets. In this work, we proposed a sophisticated combination of crop type, growth stage, and weed. Additionally, it is already in place where we will address the identification of diseases and offer a small forum for growers to discuss their concerns.

II. SYSTEM OVERVIEW

AgroVision is a and critical thinking tool built on top of an optimized AI model. Using a web-browser on almost any internet-connected Web device, a planter can post one image of a plant. The system then gives a quick, comprehensive report that does a 3-in-1 multi-task analysis from that image.

AgroVision has taken advantage of a three-tier architecture for maximum scalability, strong processing power and secure data warehouse.

1) Client-Side Interface (React.js): The React.js library was used to create the front end. By sending HTTPS requests (like uploading images) to the Application Tier and handling the ensuing HTTPS responses (analysis results), it controls user interactions. In order to reduce the possibility of mistakes in the user experience, the interface is made to be extremely responsive and simple.

2) Application Layer (Server): This functions as the system's central intelligence. It is implemented in Python using the Flask (or FastAPI) framework. It manages all Read/Write operations with the Data Tier and acts as a REST API, listening for incoming requests from the client layer. Above all, it runs the AI model for inference and contains the essential business logic.
3) The Data Layer: Our relational database, PostgreSQL, functions as the application's long-term memory. User accounts, farm bios, and previous analysis results are all securely stored in this tier, which handles data requests from the server. We are developing the entire platform using Agile methods to maintain development flexibility and responsiveness to needs.

III. PROJECT MODULES

1) *Module 1: Growth Stage Identification*

This AI module was created to provide growers with a cutting-edge technology. The AI system recognizes the crop species, its current growth stage, and any competing weeds when you upload a picture of your field[2]. Throughout the season, you can make last-minute changes to your farming strategy by keeping an eye on the diagnosis of crop by our AI systems. Compared to conventional methods, this proactive approach guarantees a much higher yield and a healthier harvest[5].

Inner Workings: To analyze morphological traits like leaf count, plant height, and flower presence, the system uses computer vision (CNNs, like ResNet or Inception).

Model Workflow:

Input: The user takes a high quality image of the Crop to upload onto our platform.

Processing: The system has a database of growth stages unique to that crop species. The temporal data is compared to the features extracted from the images by the AI model.

Output: The system determines the current growth stage (such as "Flowering Stage") of the plant. Then estimating how long it will be until harvest.

2) *Module 2: AI Chatbot*

This AI is like a trusted helper for your farm. You can describe about the problems you're having in the field, and it will look at your data and tell you where you have been doing certain things wrong. The AI can tell you what Pesticides should be used for detected outbreak. When to plant based on the weather forecast and much more. The chatbot can deliver instant, automated analysis and highly accurate data of your crop's health just by taking a picture[2].

AI Consultation Engine (LLM + RAG): This module uses advanced LLM’s, like Gemini or GPT-4. The context delivery is handled by Retrieval-Augmented Generation (RAG) framework. This framework has a full library of everything farming related like books and research papers that you can search through.

Input: The user can ask a question in their native language like Marathi or Hindi.

Logic: In the first fetch the system gets real-time data from the Growth Stage Module and Weather API. It then checks it against the RAG-enabled knowledge base. It makes sure that the advice is both scientifically correct and relevant to the situation.

Output: Multimodal delivery (text or voice) that gives practical and applicable advice for farming.

3) *Module 3: Video Analysis of Crop*

Instead of using just one picture, this module uses a short video (5 to 10 seconds) of the plant. The system takes several pictures from the video, from different frames. The lighting varies a little, and the plant is shown from a few different angles. All of these frames are looked at together[5]. By combining the results of this series of images, the system can make a more certain and reliable decision. This then avoids false negatives that might happen with just one small bad image.

These are the mechanics that make YOLOv8-seg (Segmentation) or Optical Flow work. It looks at video frames as they come in. It then count crops, read weed density, or keep an eye on problems that are happening in a specific area.

Full Model Flow

Data: Approximately 10–30 second of video snippet the user can upload as a data.

Logic: Inference The system captures frames, does object tracking to prevent double counting and accumulates throughout the video.

Output: A summary report of the crops and field (e.g., "Mean density 15 plants per sq. meter detected; 5 weed infestations were visible") is presented to the user.

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4) Module 4: Crop Disease Detection.

This is main part of the system. It uses a type of deep learning architecture named Convolutional Neural Network (CNN) to learn on the data. It trains itself on how to spot the visual signs of common crop diseases[1]. One part of this module looks for abnormality in the crop shown in the video. It analyses traits such as leaf spots, discoloration, wilting and other textural irregularities. The system identifies the disease and makes a diagnosis by comparing the abnormal patterns in the crop. This helps farmers understand how healthy their crops actually are.

Full Model Flow:

Logic: The model learns the patterns that are associated with certain pathogens. It can cross-references this with soil data to confirm that the "yellowing" of the crop is not just a sign of nutrient deficiency.

Output: Name of the disease, confidence score and suggested procedures.

IV. LITERATURE REVIEW

A research study conducted in 2025 offers a model for improving crop based advice and farm sustainability. The study proposed combining deep learning technology with big data analytics integration to vastly improve the results [3]. A similar study conducted in 2024 demonstrates the relevance of crop disease diagnostics for increasing agricultural sustainability and food security[4].

The experimental study showed that combining ML with the agriculture can show promising results. However, further improvement and study is still required in this field. The industry particularly falls behind when it's regarding enhanced feature selection and the development of new models [5].Potential of combining machine learning with agriculture for Crop Yield Prediction (CYP) is huge. Although further improvement is required. Effective CYP is highly dependent on finding the fewer, best-performing features, with future work needing to concentrate on Deep Learning model development and temperature variation analysis [8].

A study conducted recently showed that Deep Learning models perform optimally when it comes to weed detection and categorization. It is primarily due to advanced supervised learning strategies and pre-trained models.[6]. However, realizing commercial potential requires trusted, accurate and vast database. This Paired with effective supply chain management can improve farmers financial condition drastically

V. METHODOLOGY

A. Dataset Preparation

We sourced the data from a public dataset "New Plant Diseases Dataset"— accessible on Kaggle—was used in the study. The data set is an enhanced version of the "PlantVillage" dataset. The size and diversity of the dataset are increased through the augmentation. There are about 87,800 high-resolution photos in the file. These pictures are classified into 38 types. These classifications consists of 26 distinct diseases and categories of healthy leaves. It represents 14 different plant species. The information has already been divided into three separate pieces. Better data facilitation for model training is the outcome of this.

TABLE I. DATASET DETAILS

Subset	Number of Images	Number of Classes	Percentage (%)
Training	70,295	38	~80.0
Validation	17,572	38	~20.0
Test (Inference)	33	38	< 0.1
Total	87,833	38	100.0

B. Data Splitting

The data is structured in three distinct subsets to facilitate model training, testing, and validation. The pre-split follows *80/20* ratio of training and validation data.

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The distribution of the dataset is as follows:
- Training Set: Contains *70,295 images* (approx. 80% of the data)
- Validation Set: Contains *17,572* images (approximately 20% of the data).
- Test Set: A separate, small folder of *33* images is provided for final model prediction.

C. AgroVision Architecture

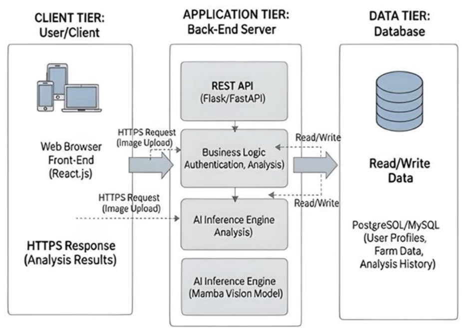

Fig 1. Architectural Diagram Of Agrovision Platform

1) User Authentication & Management : This module handles user registration and secure login and managing user access permissions.
2) Image Analysis Module: This is the core engine which processes the images uploaded by the user . Whenever a user submits a photo the system applies various algorithms to extract various features from the data. This featured extraction is powered by Vision Mamba. The module extracts key features and identifies trends. In the field of agriculture, this greatly helps in instantly evaluating crop health and soil condition.
3) Deep Learning & Computer Vision : This is the technological foundation of the image analysis system. By utilizing advanced Deep Learning models, we train the software to recognize complex patterns within large datasets. With the help of Computer Vision, technology the system can automatically detect shapes, colors, textures, and objects with a level of precision that is unmatched by any trained human eye.
4) Vision Mamba (ViM) Architecture: To achieve optimum performance the system utilises vision mamba. Vision mamba excel at understanding complex relations and patterns with an image to extract data which is useful to the model. Compare to traditionally used computer vision architecture is like vision Transformers, it is much more faster and can handle large images as it is much more memory efficient.
5) Multi-Task Analysis : To save time and cost, the AI perform multiple types of analysis simultaneously from single image. For example, one photo can be used to identify the crop species, weed density in the crop and determine the exact growth stage of the plant.
6) Results Dashboard & Reporting: In countries like India, the penetration of advanced technologies like AI & web is lower than the western countries. This creates a technological barrier for farmers to adopt to our platform. To counter this we created a user friendly interface to help them easily navigate through the website.
7) Decision Logic Algorithms : Running on the backend server, rule-based algorithms interpret the raw data output from the AI. These algorithms then deduces practical, actionable solutions tailored to the user and its local climate.

D. Multimodal Fusion

The multimodal fusion is an emerging technology that is defining how we detect diseases. Multimodal Image Fusion integrates data from multiple sources into a high quality image that minimizes redundancy[9]. Although the traditional disease identification method was based on a single image analysis has shown optimal results in some specific fields, its diagnostic accuracy and comprehensiveness are often limited[11].

Theoretical basis

a) Convolutional Neural Networks

A Japanese scientist invented Convolutional Neural Networks (CNNs), which are essential models in deep learning and particularly well-known in computer vision for image processing applications. CNNs are excellent at automatically extracting features, in contrast to standard techniques that require substantial data pre-processing for complex datasets. Because of their innate ability to automatically learn features, this characteristic makes them a popular method for data analysis. CNN is a machine learning method that, in essence, is a quite complicated function that directs the model to carry out tasks like classification and segmentation by identifying mapping relationships in data.

Extracting feature representations from picture data is the function of the convolutional layer. The fully connected layer is utilized for the linear combination of final features, while the pooling layer reduces the dimensionality of features to lower the number of parameters in subsequent networks. The neural network gains the capacity to fit real-world data by mapping the activation functions following the convolution and pooling processes. The neural network employs one or more fully connected layers to extract feature maps after multiple successive superposition of convolution-pooling modules. These layers are then randomly combined to acquire the best features in the final classification, which is the network's output.

b) Transformers

In the realm of Natural Language Processing (NLP), the Transformer model was introduced in 2017. Furthermore, their Transformer basically takes a sequence as input and outputs a sequence model (sequence to sequence). Inspired by Transformer, Dosovitskiy et al. introduced Transformer architecture to computer vision and created Vision Transformer based on computer vision data characteristics. Additionally, this discovery has motivated several researchers to use Vision Transformer in their respective domains. Transformer has demonstrated excellent performance in several common computer vision tasks.

Vision Transformer's usage of the attention mechanism, which differs from the convolutional neural network's feature extraction method, is primarily responsible for its exceptional performance in the field of computer vision [12]. The Vision Transformer model design uses the scaling dot-product attention mechanism.

VI. RESULTS AND DISCUSSIONS

A. Plant Disease Identification

Finding a balance between cutting-edge AI and practical, field-ready application was the core of our AgroVision project. Our primary objective was to create a robust early-warning system inside our multi-modal platform so that the growers around the world could take care of their produce much better.

The first step in developing our plan was gathering the relevant data of the crops. For that to happen we required a sizable and diverse collection of agricultural pictures. As our main training set, we chose to utilize the popular PlantVillage dataset. It is then processed and used to train a simple yet effective diagnostic model.

In terms of the fundamental architecture of our platform , we made sure to abide by the fundamental idea of simplicity, scalability and security. The entire AgroVision platform uses the state-of-the-art Vision Mamba (ViM) architecture, which we used to achieve an appreciable 97.1% accuracy for more complex tasks like image analysis tasks like growth stage and disease identification. Because CNNs are inherently adept at extracting spatial data, we decided to employ a CNN-based approach for this module. They are highly successful in identifying even the tiniest abnormalities on a leaf's surface.

B. Growth Stage Identification using Deep Learning Techniques

There are 2 main approaches made to identify plant growth stage, listed as

a. Generic deep Learning Framework for growth Stage Identification

To this day, the deep Learning structures can be classified into two categories, the first one being pure CNN based network and second is the hybrid CNN-LSTM approach towards growth stage identification[14]. In pure CNN networks, the data is fed to the network in the form of black and white 2-D images of the crop, which only provides spatial information and lacks the temporal aspect of plant growth monitoring.

b. Hybrid Approach To Plant Growth Stage Monitoring

CNNs with convolutional layers have been widely employed in DL architecture applications to produce meaningful spatial representation of multidimensional data in image-based plant growth monitoring, which mostly consists of decision-making based on information collected from images. However, spatial information shouldn't be the only factor taken into account during the monitoring process because plant growth may also be seen as a sequence of events that unfold over time in a plant life cycle. In particular, a hybrid DL architecture that combines CNN and LSTM offers the potential to more accurately interpret the plants' spatial-temporal characteristics.

C. Virtual Assistant powered by Google Gemini

Google Gemini stands as the most capable LLM model till this date, designed to tackle complex task with unmatched efficiency and accuracy. Google Gemini operates through a popular deep learning architecture of encoder-decoder providing natural language communication capabilities [15]. Additionally Gemini operates on a "Multi-expert System", making it efficient at handling various tasks simultaneously[16].

a. Tokens and Temporal Context Handling

Traditional large language models (LLMs) processes, Data by converting input into units called tokens[17]. These tokens represents various grammatical concepts like punctuation, tense, words, letters etc.[18]. Token limit is the term that represents the number of tokens we can send to Gemini to process at a single time. As a State of the art LLM model Gemini can process upto 1 million context tokens at the same time. This huge context window helps our platform to store and manage temporal data more efficiently

TABLE II. GEMINI PERFORMANCE METRICS

Metric Type	Task Content	Performance level
Precision	Data extraction	Show nearly 15% Improvement over GEMINI 2.5 Flash
Recall	Long Context	In MRCR v2, it maintains a recall score of 0.77 over the context window of 128k tokens
F1 Equivalent	Factuality	It's "closed book" knowledge accuracy sits at 72.1%, which still can introduce hallucinations if not allowed to search the web

b. Multilingual Capabilities of System

- Native Multilingual Comprehension

The GEMINI is capable of handling text generation as well as processing tasks using the full gamut of languages available. Therefore, GEMINI can interpret any subtle language nuances used by a farmer who speaks in his native tongue and relate that to agriculture-related information in science.

- Context-Aware Technical Translation

In translating farm information and advice, there needs to be high accuracy in the translations to prevent costly errors. Unlike other machine learning models which work on smaller context windows to translate sentences, the GEMINI work on large context windows so that the thread of the diagnostic process remains intact throughout. Thus, the GEMINI model can extract information from the English research papers stored in the RAG database and provide scientific insights in Marathi.

GEMINI Can Process

- 40+ Core Languages & 70+ Languages for Live Audio: Including Regional Languages of India, like Marathi, Tamil, Telugu, Malayalam, Gujarati.

D. Final Results

The model's final performance is mentioned in detail through Table III. The model achieved an excellent weighted-average F1-Score of 0.971. This proves the effectiveness of the ViM architecture for this task.

However, the model's performance was not uniform. While it achieved good scores for identifying healthy plants, it struggled with visually similar diseases.

TABLE III. MODEL PERFORMANCE METRICS

	Precision	Recall	F-Measure
Macro-Average	0.970	0.969	0.969
Weighted-Average	0.971	0.971	0.971

TABLE IV. EXPERIMENT RESULTS

Study	Model Used	Dataset	Accuracy (%)
Reddy & Kumar [1]	Custom CNN	Local dataset	94.5
Sankaran et al.[13]	SVM	14-class PlantVillage	95.0
Li et al. [5]	ResNet-50	38-class PlantVillage	98.2
Our Work	Vision Mamba (ViM)	38-class PlantVillage	97.1

Experimental results have proven that a multimodal AI-based scheme has achieved better performance than image-only approach in complex agricultural situations.

- Complementarity of information: The visual data is used to detect the symptoms of the disease (e.g., leaf chlorosis) while the chatbot provides insights that requires decades of expertise.
- Robustness in Multi-Crop Analysis: The model retained its high predictive accuracy on intercropping, too, verifying that it can be easily adopted for various cropping systems.
- Operational Efficiency: With an average inference latency of 25–40 ms, the system can be deployed very fast even on devices that have low compute.

E. *System* Limitations *& Future Enhancements*

While AgroVision demonstrates good performance in controlled environments, real-world probing has uncovered a few operational limitations.

- Environmental Extremes: The model can hallucinate under extreme contrast and heavy occlusion (e.g., overlapping foliage or dense weed canopies). Though this happens very rarely.
- Hardware & Connectivity: Processing high-resolution video clips requires stable internet connection. This is the factor which is often limited in rural agricultural zones. Additionally, running complex multi-task inference can drain battery life on older weaker mobiles.
- Future Implementations: To mitigate these challenges, future iterations will incorporate stronger data augmentation. We also plan to explore the integration of infrared/multispectral imaging to bypass visual occlusion. We are developing an "Offline Edge Mode" to allow basic diagnostics without an active internet connection albeit will require a modern phone with stronger GPU.

VII. CONCLUSION

Farming is one of the world's oldest and most important jobs, but that doesn't mean it can't benefit from a little modern help. That's why we created AgroVision. We’ve built an easy-to-use web platform that puts advanced AI directly into the hands of farmers everywhere.

Our goal is simple: we want to help growers take the guesswork out of farming. Instead of just reacting to problems as they pop up, AgroVision gives you the clear, practical insights. By helping farmers see exactly what their crops need, they can save money, waste fewer resources, and ultimately grow more food.

To make this happen, we use advanced AI technology called Vision Mamba (ViM)—but farmers don't need to be a tech experts to use it. While older tools usually only let you tackle one problem at a time, AgroVision acts as an all-in-one assistant in a single place.

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