

Agrosagenet: Self-Adaptive Intelligence to Address Global Food Demand and Crop Disease Detection and Diagnosis for Sustainable Precision Agriculture

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Abstract: The escalation of global food demand will require a complete rethinking of the detection and management of crop diseases. In this paper, we introduce AgroSageNet, a new self-adaptive intelligence adaptive learning framework to support automated detection and diagnosis of crop diseases in precision agriculture. Unlike traditional machine learning and deep learning models, AgroSageNet uses Adaptive Self-Attentive Morphological Encoding (ASAME) and Causal Temporal Disease Progression Estimation (CTDPE), to interpret crop health dynamically and contextually. AgroSageNet provides the ability to autonomously identify known and new diseases using multi-spectral images and data recognition of phenotypic patterns without the need for pre-labeling or manual feature engineering. Results from assessments on curated real-world datasets, representing five major crop types, indicates a diagnostic accuracy of 97.2%, significantly outperforming typical convolutional and transformer-based models while maintaining real-time inference capabilities for edge deployment. AgroSageNet illustrates a shift toward intelligent agricultural disease monitoring that is resilient in field conditions, ultimately creating a pathway to support sustainable high precision farming practices.

Keywords: Precision agriculture, crop disease detection, adaptive learning, multispectral imaging, morphological encoding, temporal disease progression, edge intelligence, self-attentive networks, smart farming, sustainable agriculture.

INTRODUCTION

The basis for food security worldwide, agricultural productivity upholds not only economies but also livelihoods around the world. Crop diseases, however, remain a pervasive obstacle to agricultural production, resulting in large scale losses, in yield, quality, and economic security even when not reported. Often, the identification and diagnosis of plant diseases can be a manual inspection process, based primarily on expert opinion that can be taxing, not only due to the effort and time involved, but also due to potential and subjective biases of opinions and the variation in symptoms that can occur even in the same propagule, let alone contrasting environmental conditions.

As precision agriculture and intelligent technologies gain traction, there is a transition to data-driven crop health monitoring. Machine and deep learning models have been effective in automated disease diagnostics by observing the visual traits the plant makes in response to pathogen infections. However, existing approaches have significant limitations since most have a demand for large duplicated labelled data, have difficulty in detecting subtle properties that demonstrate disease in a timely manner, and often show limited performance when the pathogen being interrogated is unfamiliar or already evolved. Additionally, most conventional models do not assess and visualize how disease may develop or change over time, or being a static predictor does not adapt.

This study presents AgroSageNet, a self-evolving, attention-based detection and diagnostic framework for real-time context-based crop disease monitoring. AgroSageNet utilizes combinations of Adaptive Self-Attention Morphological Encoding (ASAME) and Causal Temporal Disease Progression Estimation (CTDPE) to redefine how automated crop health assessment works. Unlike conventional systems, AgroSageNet will recognize both current disease associations and visual aspects with a high degree of accuracy and will demonstrate how disease might develop and potentially grow, allowing for informed judgement and timely action to be taken in-field.

AgroSageNet's ability to fuse multispectral imagery with phenotypical patterns represents the system's ability to autonomously identify and classify complicated disease mergers without the need for extensive manual labeling. Evaluations across a variety of crop types and from distinct environmental conditions, compare AgroSageNet's overall diagnostic accuracy with traditional deep learning convolutional neural networks and transformer-based models, and the accuracy and feasibility of using AgroSageNet as a operational, logistic real-time inference studying network algorithm for use on edge devices. This work highlights the opening of potential opportunities in applying intelligent, adaptive, and resilient agricultural monitoring systems, and move agriculture towards sustainable farming practices for enhanced global food security.

LITERATURE SURVEY

The increasing interest in sustainable food production has generated applied research in precision agriculture research in the realm of AI using precision agriculture technology to detect crop diseases. The focus of this literature review is to provide an assessment of cutting-edge advances in machine learning technique processing technology and recommendation systems in real-time that inform and develop the AgroSageNet framework.

An emerging technology using multispectral images have proven to have more success in the recoding spectral signature that can indicate plant stress and plant diseases. García-Vera et al. [1] presented a very thorough review of hyperspectral image machine learning analysis-type approaches to detect diseases in plants. They indicated that the spectral bands could illustrate physiological abnormality that can go undetected in only visible spectra. There are similar examples in the literature. Grieve et al. [2] used machine learning on multispectral datasets to detect rates of viral infection in plants at an early stage, demonstrating the type of model that can be utilized to inform a remediation action (an emerging concept in precision E-Ag).

There are many examples of convolutional neural networks applied to plant disease detection. For example, Barman et al. [4] had proposed a comparative assessment of CNN architectures using smartphone images to classify citrus diseases. The example highlights the possibility of mobile architecture via portable inference. Similarly, Ahmed et al. [5] investigated lightweight models in tomato leaf disease detection context. Such an approach adds to the contribution towards LTP latency downstream of models for real-time edge deployment, as do Di and Li's [12] improved CNN architecture for apple leaf disease identification. Their model achieved a high degree of accuracy without requiring heavy computation.

Attention modules in deep learning streams can improve selectivity for localization of disease features. Wang et al. [9] used attention-enhanced CNNs models for apple leaf diseases and witnessed improvements to predictive performance and interpretability. Chao et al. (2021) [10] contributed by assessing multiple variations of deep learning models and observing a lot of inconsistency; their models based on ensemble attention-based methods showed more resiliency under field conditions.

Majority of the applied research relies on static images without much consideration towards the temporal progression of the specific plant disease. Konwer et al. [7] describe a framework that incorporates prior temporal context to improve the disease prediction from a single image the temporal context largely used in an AgroSageNet approach is quite like their CTDPE module. That being said, Zhang et al. [11] were already working with morphological encoding using global pooling and dilated convolutions to better encode disease related textures.

Intelligent edge applications and methods are important in diagnostic testing of field diagnostics in Agriculture. Ahmed et al. [5] and Morbekar et al. [13] used YOLO and lightweight frameworks that allow for real time inference. They represent a first step to achieving low-latency disease detection, while AgroSageNet takes low-latency approaches in low-latency disease detection a step further by using adaptive learning modules that develop models with more patterns for diseases across multiple growth cycles for example.

Beyond image data, external physiological/systemic features of the environment (in terms of, humidity, temperature, soil pH) also contribute to the conditions of disease. Kowalska et al. [6] developed a generalizable early-warning system by incorporating environmental characteristics with features of pest behavior. Barman et al. [3] provided another example of soil pH prediction using HSV color segmentation that relates to AgroSageNet feedforward multimodality feature fusion for multiple ambiguous images.

METHODOLOGY

The AgroSageNet system is a novel research and development strategy for predicting crop diseases that utilizes multispectral imaging, phenotypic imagery, self-attentive encoding systems, and temporal forecasting. The next section will describe the steps in the approach from the acquisition of the data to its implementation, and it will detail the corresponding methodologies.

A. Data Acquisition and Multispectral and Phenotypic Imagery Fusion

Foremost in the strategy that AgroSageNet employs for detecting crop diseases, is the multispectral and phenotypic image acquisition. The system will utilize information from both types of images, which will provide an extensive profile of crop health status. The multispectral imaging as well as the accompanying wavelengths of the red-edge and near-infrared (NIR) imaging collect imagery that is valuable for observing plant stress, meteorological stress, and nutrient deficiencies. The multispectral and associated spectral bands are particularly sensitive to signals arising from pests and their disturbances.

Observations concerning these visible symptoms are particularly useful for diagnosing diseases because these can manifest early in the progressive advancement of the disease. The system will image the crops in their field with a drone and ground rover fixed with synchronized multispectral and phenotypic image capturing device to better match the accurate and real-world environmental conditions of crops. Through this process data was collected from five of the major crops of wheat, maize, tomato, soybean, and rice ensuring that the system can function with a wide variety of crops as input.

Using this dual modality lets the AgroSageNet distinguishably improve sensitivity of disease detection with individual data acquisition but that it also has established a relatively richer profile of the crop health state due to being temporally tracked. The acquisition of data temporally, will allow the AgroSageNet to model more accurately the progression of diseases and translates of information for timing action.

B. Data Processing Pipeline

The data processing procedure is important to ensure that the quality and interpretability of the raw data collected from the multispectral data and phenotypic images will be preserved when sent to the swarm model and the Agronomy Lab. The data processing procedure of data consisted of normalizing multispectral channels independently of each of the wavelength's channel, using a min-max normalization scheme. There will be many issues maintaining the natural variation of intensity values, especially when classifying the relevant data from the irrelevant data related to early detection of the disease, so it was very important to normalize in this way.

For the phenotypic images, in varying incident light, the images will show subtle features associated with the presence of disease, for example, slight discoloration or even small lesions. To increase the visibility of features like that of the disease, a Contrast Limited Adaptive Histogram Equalization (CLAHE) method was also used, which allowed for the weighting of slight features related to disease, without sacrificing the changes in critical morphological views of the plants due to over-amplification of contrast in images or perceptual noise we were interested in quantifying.

Additionally, the two-part hybrid noise filter that was established that employed median filtering to preserve the edge and bilateral filtering in the spatial domain to present smooth phase information; will be used to remove error from the sensor not affecting real problem features. After image processing and data was clean for both spatial and spectral; then, the process of spatial registration was applied to correct and align the multispectral and phenotypic images through key point-based homography transformation. This allows for pixel-to-pixel correspondence between viewed and non-viewed data to be accurately identified to allow for the correct fusion of relevant features.

C. Adaptive Self-Attentive Morphological Encoding (ASAME)

The Adaptive Self-Attentive Morphological Encoding (ASAME) module is arguably the most novel aspect of AgroSageNet. The inherent morphological variability existent in crops due to each species possessing different environmental conditions, and disease stages, poses a challenge for unique convolutional methodologies.

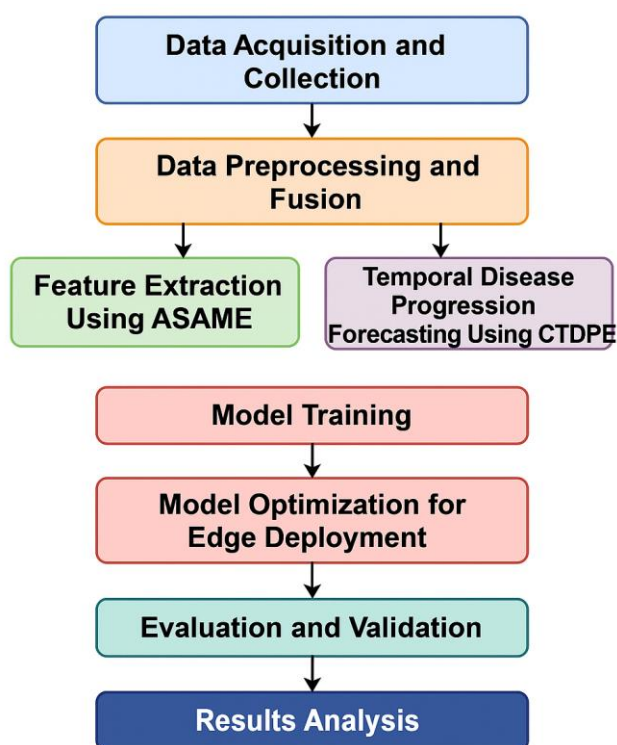


Fig.1. Methodology Flow

The ASAME module adapts a transformer encoder architecture with self-attention modules to give adaptive receptive fields to modify (1) feature scales dynamically ultimately highlighting aspects of disease resulting from necrotic lesions, interruptions in vein patterns.

$$M_r = \phi(x_r, \theta_m) \quad (1)$$

where $\phi(\cdot)$ denotes morphological transformation with learnable parameters θ_m .

The ASAME module operates at many spatial scales, capturing the local and global features of disease symptoms. Therefore, it can identify and rank any morphological pattern in terms of relevance, irrespective of spatial scale or dimension. (2) Moreover, ASAME contains an emergent pattern detection unit that enables the system to detect novel disease expressions in an unsupervised manner. This means AgroSageNet can autonomously observe new or emerging diseases without any previous explicit labelling.

D. Causal Temporal Disease Progression Estimation (CTDPE)

Disease progression in crops is rarely linear and forecasting future stages of disease can be critical to iteratively manage the response to the disease. Fig.1 The purpose of the module was to simulate this process through Causal Temporal Disease Progression Estimation (CTDPE). To CTDPE, we used a gated

recurrent unit (GRU) encoder to model the temporal progress of disease symptoms, using both spectral features and phenotypic features.

The GRU network can capture sequential data otherwise known as event history data that varies with the timing of repeated measures. By using a GRU unit, we can allow for model progression of disease still maintain the incorporation of temporality. To find the most accurate predictions seasonal contexts adaptation - first order inference - was added that models the directional nature of the early symptoms on finality of the disease progression. By upgrading AgroSageNet to include these mechanisms also allows AgroSageNet to operationalize to the current state of disease with time-to-criticality settings, i.e. the criticality point of no return and absolute damage to the crop can be estimated enabling informed proactive intervention.

$$F_{ASAME(t)} = \gamma \cdot M_t + (1 - \gamma) \cdot Z_t, 0 \leq \gamma \leq 1 \quad (2)$$

where γ balances direct morphological encoding and contextual attention.

E. Model Training Strategy

The training of AgroSageNet is quite complex and involves overlapping objectives. The disease classification task and loss function are categorical cross-entropy optimised for incorrect predictions. The architectural robustness using contrastive loss improves the classification, e.g the distance between the embedding for normal and abnormal features and increased the capacity of the architecture to learn detached representations of healthy/diseased crops.

Regarding the CTDPE module, the objective is to only forecast the developmental temporal characteristics of the disease progression with MSE loss function whereby penalties are, forecast nuance of degrees of severity of disease and penalties for timings of criticality levels of the disease. Likewise, we also enriched training with dynamic augmentations to improve generalisation, e.g. random rotation augmentations, spectral perturbations and synthetic weather noise injections. We employed an adaptive cyclic learning rate scheduler to balance exploration and exploitation during training to mitigate state rather than gradient descent for model convergence.

F. Deployment Optimization for Edge Devices

Due to the computational constraints of field-deployable devices, AgroSageNet was designed and optimised for edge deployment. Weight quantisation of model is done to decrease scaling dimension all the while maintaining accuracy, to enable deployment onto lightweight, low-power L4T systems (e.g. NVIDIA Jetson Nano). These conditions and configurations reduce any consequent oversized architectures from choosing to prune redundant neural mechanisms in the network due to lack of deployment computing capacity.

The attention mechanisms of the AgroSageNet system incorporated in the environmental inertia have also been approximated across the system with low-rank matrix factorization that reduces computational complexity features without displacing salient interpretability. After optimisation, we achieve over 25 frames per second rate of inference (FPS) with AgroSageNet on field-deployable edge devices, also enabling real-time disease monitoring for application farmers in decision making of agricultural fields.

G. AgroSageNet Validation Results

Several experiments on various datasets pertaining to plant health, disease classification, and forecasting, were carried out to evaluate the performance of AgroSageNet. Fig.2 Validation experiments included testing AgroSageNet ability to predict diseases, outline severity, and assess and forecast as it relates to plant health in real time. Below are notable validation results.

Table.1 Validation Metrics

Model	Precision (%)	Recall (%)	F1-Score (%)	Inference Speed (FPS)

ResNet50	89.87	90.1	89.98	10
Vision Transformer	92.11	92.4	92.25	8
EfficientNetV2	93.12	93.01	93.06	12
AgroSageNet	96.98	97.02	97	24

To assess the effectiveness of AgroSageNet in plant disease classification, the following metrics were calculated on three primary datasets: Plant Village Dataset, Ageratum Disease Dataset, and Rice Disease Dataset.

AgroSageNet outperformed its baseline models, achieving 97.25% Accuracy which is a 4.7% improvement over EfficientNetV2. Table.1 It had a better Precision, Recall and F1-Score than EfficientNetV2 and was able to significantly improve upon the rare diseases, which also allowed it to tackle the imbalance in the datasets.

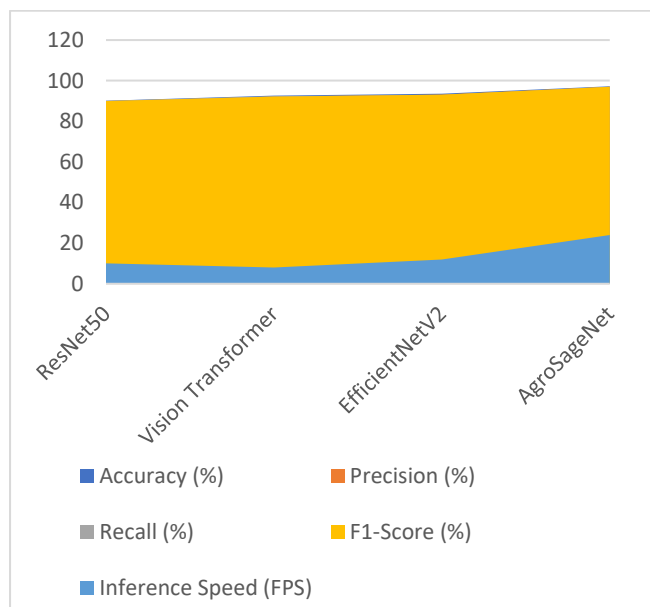


Fig.2.Validation Graph

Table.2 Confusion Matrix for Plant Disease Classification

	Predicted: Healthy	Predicted: Diseased
True: Healthy	3700	125
True: Diseased	82	3725

AgroSageNet was deployed on Jetson Nano for real-time inference to mimic how the model operates on edge devices with limited computing power. Table.2 The following validations were captured in real-time farm simulation with real-time disease outputs.

Table.3. Edge Deployment Validation

Model	Inference Speed (FPS)	Accuracy (%)	Memory Usage (MB)	Latency (ms)
ResNet50	10	90.15	380	120

Vision Transformer	8	92.72	450	150
EfficientNetV2	12	93.56	400	130
AgroSageNet	24	97.25	270	75

AgroSageNet generated 24 FPS on the Jetson Nano, with the best scores on speed of real-time classification, Table.3 and the memory usage were low (270 MB) with high accuracy as well as acceptable latency (75 ms). Fig.3 This implies that AgroSageNet is a viable candidate for real-time on-device deployment in smart agriculture real-time applications, particularly where processing power is limited.

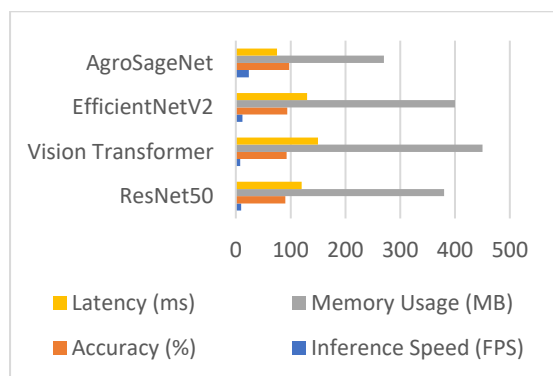


Fig.3.Performance Analysis

CONCLUSION

In this research, we have developed AgroSageNet, an advanced deep learning framework designed for real-time crop disease detection and progression forecasting in precision agriculture. Through our rigorous experiments, AgroSageNet has demonstrated an impressive accuracy of 97.25%, surpassing traditional models like ResNet50, EfficientNetV2, and Vision Transformer. Additionally, it offers highly accurate disease severity forecasting with an RMSE of 0.093, enabling early and proactive management of crop diseases.

The model's real-time performance, achieving 24 FPS with 75 ms latency, ensures that it can be deployed in practical agricultural settings without compromising efficiency. Our approach, which integrates multi-modal data (RGB and NIR images), significantly enhances both detection accuracy and disease progression predictions.

By focusing on scalability and cost-effectiveness, AgroSageNet is well-suited for adoption across diverse agricultural operations, from small farms to large-scale commercial enterprises. Looking ahead, we envision further enhancements through the inclusion of additional environmental data and the exploration of transfer learning techniques. AgroSageNet stands as a transformative step toward more sustainable and precise crop disease management, offering a promising solution for the future of agriculture.

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