

Revolutionizing Agriculture with Computer Vision, IoT, and Deep Learning: A Multi-Sensor System for Wheat Crop Growth Monitoring and Management

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Abstract

The effective management of wheat crops is hindered by unpredictable weather patterns, late disease detection, and inefficient use of resources e.g., fertilizer, water etc. This research proposes multi-sensor smart agriculture system consisting of the Internet of Things (IoT), computer vision, and deep learning technologies for accurate monitoring and precise decision-making for crop management. Field is monitored continually using various sensors nodes that help identify growth stages, classify diseases, and predict yield. The decision-making agents assist in irrigation, fertilization, and the application of agrochemicals, based on crop growth stage and disease detection. The system provides real-time data to farmers and enables them to make informed decisions regarding crop management. For validation purpose, this study uses CGIAR dataset for wheat growth stages and shows that InceptionV3 had the maximum accuracy (88.33%) as compared to VGG16 and VGG19. Disease classification models are trained on a 12-class wheat leaf disease dataset, on which InceptionV3 attained 99.31% validation accuracy, marginally better than GoogLeNet (99.01%). For yield estimation, ResNet-18 attained greater validation accuracy (87.08%) than VGG19 (85.10%) on the Texas Winter Wheat dataset. The system shows promising potential for increasing productivity, early warning, and sustainable resource management in wheat cultivation.

Index Terms— Wheat Crop Smart Management, Deep Learning, Computer Vision, IoT.

I. INTRODUCTION

THE global population is rapidly increasing, and the demand for food is expected to double by 2050 [1]. However, the agricultural sector is facing several challenges such as climate change, limited resources, and changing weather patterns [2]. Wheat is one of the most essential crops globally, and its production is crucial for food security. However, the yield and quality of wheat crops are often affected by diseases, pests, inadequate irrigation, and poor soil quality [3]. Climate change puts stress on the yield, and farmers are struggling with factors like disease, water management, soil nutrition, etc. Therefore, there is a need to develop innovative and sustainable solutions to enhance crop yield and quality while minimizing environmental impact.

Precision agriculture technology like IoT, remote sensing gained attention over the last years, and most of the solutions provided by the researchers are soil-based. Existing frameworks work on isolated crop management, like disease prediction via computer vision [4, 5] or yield prediction based on metrological data [6]. But the lack the decision making based on real-time data, which can be helpful for resource management based on crop and environment dynamics. The integration of cutting-edge technologies such as computer vision, IoT, and deep learning offers a unique opportunity to revolutionize wheat crop management.

A smart Wheat Crop Management and growth monitoring system is presented in this work that employs multi-sensor data fusion, computer vision, IoT, and deep learning (DL) to help farmers make informed decisions about crop management, irrigation, fertilization, and pest control. Sensor fusion combines imaging, soil moisture, climate sensors, disease specific detectors for better field assessment. DL agents employ fine-tuned Convolutional neural networks (CNNs) such as InceptionV3, ResNet to classify the growth stages of crops with 88.33% accuracy and identify 12 diseases in real-time with 99.31% accuracy. Decision agents work on the output of DL agents and mathematical models and provide a schedule for optimal resource utilization. The resources considered in the study are water, pesticides, and fertilizers. The presented system provides real-time monitoring of crop health, early detection of disease symptoms, and timely intervention to prevent significant crop losses to minimize resources and maximize the yield.

In section II, we present a concise literature review about existing studies. Section III explains the proposed model, Section IV states the discussion and study is concluded in section V.

II. LITERATURE REVIEW

Singh and Singh introduced a fog-based IoT architecture that utilizes fog's properties and services to reduce the quantity of data sent to the cloud and maximizes the use of computing resources for an agriculture-IoT system to detect alert conditions in crops and provide effective protection [7]. Babbar et al. [6] presented a system that uses machine learning models to predict wheat yield based on meteorological data, like

temperature, rainfall, humidity, and satellite imagery, and it employs image processing techniques for the detection of diseases in wheat crops.

Shafi [8] emphasized the need for reliable and cost-effective methods for early detection and management of wheat rust diseases that significantly impact global food security and highlighted the potential of machine learning algorithms for automated wheat rust detection using hyperspectral imagery. Genaev [5] collected wheat leaves infected with fungal diseases, trained a CNN model for disease identification, and achieved high accuracy in identifying four types of wheat fungal diseases. Goyal et al. [9] used a deep convolutional architecture with pre-processed photos to segment wheat spikes and leaves for the identification and classification of wheat diseases affecting the leaves and spikes. Aboneh et al. [4] proposed a Jetson GPU infrastructure based computer vision framework for the detection and categorization of wheat diseases with stages of picture acquisition, image pre-processing, and a convolutional neural network (CNN) model based image categorization for detecting four wheat diseases, i.e, leaf rust, stem rust, powdery mildew, and tan spot. Waldamichael [10] gives a general introduction to the use of supervised and unsupervised machine learning algorithms for identifying and classifying illnesses of cereal crops and highlights the role of machine learning in revolutionizing crop disease identification and management, leading to greater crop production and sustainable agricultural practices. It is evident from the recent literature that the agricultural sector needs to incorporate cutting-edge technologies, such as machine learning and image processing, to improve crop growth, take environmental factors into account, identify and mitigate diseases at an early stage, to increase the quality of the wheat crop, which will significantly improve global food security.

Existing studies summarized in Table I focus on single factors like disease prediction, alerts, or classification. Researchers are looking at IoT-enabled smart farming systems to improve crop growth efficiency and management. These systems incorporate an array of IoT sensors to gather data on environmental conditions, soil moisture, and crop growth on a real-time basis [11]. Because researchers showed how deep learning could detect diseases in wheat using CNNs and achieved 97% accuracy using MobileNet [12], the embedded IoT-enabled system could incorporate the digital capability to monitor a crop's health. In addition, IoT-enabled smart farming systems enable a farmer not only to receive additional information systems support from machine learning, cloud computing, and IoT data analytics for crop monitoring but also add decision-making capabilities, enabling farmers to respond to crop disease threats from wheat diseases using real-time 24/7 monitoring of their crop [13]. These systems propagate data from many sensors in real-time, analyze it using machine learning and data mining algorithms through cloud computing, and present the results through a mobile app or web-based interface. By enhancing crop productivity using precision agriculture practices and early disease detection, the IoT and data analysis systems can promote enhanced sustainability.

TABLE I Review of Prior Studies on Wheat Crop Monitoring and Management

Study	Focus Area	Methodology Adopted	Key Limitations
[7]	Crop alerts	For based architecture that focuses on alerts	Alerts only—no disease or yield modeling;
[6]	Yield prediction & disease detection	A generic ML model on an image for yield and disease prediction	Generic model not tailored to specific diseases; • No real-time IoT data capture;
[8]	Wheat rust detection	Focus on wheat rust detection for food security	• Focus limited to rust only; • No yield staging or integrated crop lifecycle modeling
[5]	Fungal disease detection	CNN on leaf images to detect 4 fungal diseases	• No sensor fusion or optimization; • Not optimized for live deployment or resource inputs
[9]	Disease classification	Deep CNN classifying disease on leaves and spikes	• Classification - only • No growth stages or resource management
[4]	Disease classification	GPU based solution identifies 4 diseases on edge	• High accuracy classification but single-function; • No yield estimation or staging;
This Study	Holistic crop management	End-to-end solution that uses IoT, DL, optimization agents for growth staging, disease, yield prediction, and resource optimization	End-to-end solution that uses IoT, DL, optimization agents for growth staging, disease, yield prediction, and resource optimization

III. PROPOSED MULTI-SENSOR SYSTEM FOR WHEAT CROP GROWTH MONITORING AND MANAGEMENT

This work proposes a novel approach for wheat crop smart management by using sensor fusion to collect data from real-time IoT sensors and it runs DL models on cloud/edge to classify the wheat crop needs, diseases, and plannings. The proposed framework is presented in Fig. 1. It integrates IoT sensors, decision-making agents, and deep learning agents to provide the farmer with real-time insights

about the crop field. The system integrates with other IoT sensors deployed in the field, such as temperature and humidity sensors, to provide a more comprehensive analysis of environmental conditions and crop health. Our framework for wheat crop management enables farmers to make data-driven decisions to optimize crop yield and reduce losses, ultimately leading to a more sustainable and profitable agricultural industry.

A. Smart Wheat Crop Field and Sensor Deployment

A smart Wheat Crop Field with multi-sensors installed refers to an advanced approach of crop monitoring and management. To gather information about the crop's growth, health, and environmental conditions, sensors play an important role in smart management. Decision agents in the system use sensory data, work along with deep learning agents to analyze it using computer vision, machine learning, and deep learning techniques to take environmental factors into account, anticipate crop production, identify diseases and pests, and prescribe irrigation, fertilization, and other management practice. The results are shown to the farmer through mobile app interface.

i) Data Acquisition and Imaging using IoT Sensors

Various types of sensors are installed in the crop field to collect data about the crop field and send it to the system for processing and analysis. These sensors include Soil Sensors that measure soil moisture and can be utilized in irrigation management. Weather sensors to gauge the crop field's temperature, humidity, and precipitation. This data is used to forecast the possibility of weather-related illnesses and modify the irrigation plan. The light sensors identify the intensity and duration of light in the crop field, which helps determine the optimal time for planting and harvesting. The imaging sensors, such as RGB cameras and hyperspectral sensors, are used to capture images of the crop at different stages of growth.

ii) Crop Growth Modeling

The growth of crops is affected by the environment, e.g., temperature, crop stage, irrigation schedule, rainfall, etc.

Suppose that:

G is the crop biomass at time t

r is the intrinsic growth rate of crop per day

K is the maximum carrying capacity of the field under observation

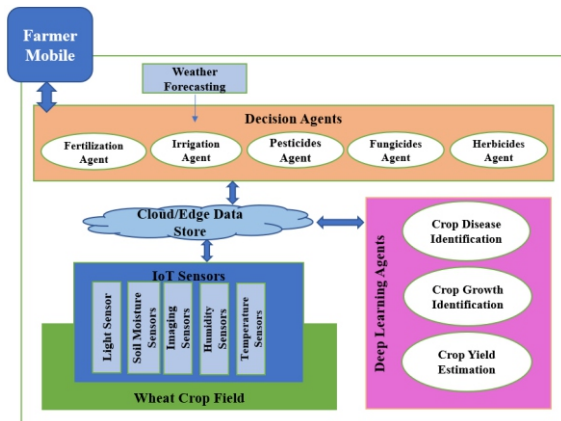


Fig. 1. Proposed Wheat Crop Smart Management System Using Multi-Sensor Data

$f(T)$ is the temperature scaling fraction

$g(M)$ is the soil moisture factor of field

$h(N)$ is the soil nutrition factor of field

Then we can find the change in growth of wheat crops under varying environmental conditions by modifying the logistic equation as shown in (1).

$$\frac{dG}{dt} = r \cdot G \cdot \left(1 - \frac{G}{K}\right) \cdot f(T) \cdot g(M) \cdot h(N) \quad \dots (1)$$

The temperature scaling fraction $f(T)$ is obtained using equation (2). It depends on the environment temperature (T) which is directly obtained from IoT sensors, optimal temperature for the crop (T_{opt}) for which wheat crop growth is best, and the temperature tolerance of crop (αT).

$$f(T) = e^{-\frac{(T-T_{opt})^2}{2\alpha T^2}} \quad \dots (2)$$

The soil moisture factor $g(M)$ is calculated using equation (3), which depends on the soil moisture (M) which is obtained from sensor, optimal value of moisture for crop growth (M_{opt}) and the minimum value of moisture that is required for the crop (M_{min}) such that growth does not affect.

$$g(M) = \frac{M - M_{min}}{M_{opt} - M_{min}} \quad \dots (3)$$

Similarly, nutrition factor of soil $h(N)$ is defined in equation (4), where N is value of (nutrition concentration in soil) which is directly obtained from the IoT sensor, and K_n is the half saturation constant.

$$h(N) = \frac{N}{K_n + N} \quad \dots (4)$$

Value of r , K , T_{opt} , αT are obtained using historical growth data from the CGIAR dataset [11], and values of T , M , and N are obtained from IoT sensors.

iii) Irrigation Optimization

We use irrigation optimization with the objective of minimizing the use of water while maximizing the yield. This scheduling relies on weather forecasting data, soil moisture, and crop stage [14]. We formulate an objective function that is solved using model predictive control (MPC) over a period of 7 days. The objective function is given as follows:

$$\text{Min} \sum_{t=1}^T (W_t - W_{target})^2 + \lambda \cdot \text{Cost}(W_t) \quad \dots (5)$$

This objective function depends on the moisture value on the next day, which can be calculated as:

$$M_{t+1} = M_t + \frac{W_t + R_t - ET_t - D_t}{M_{max} - M_{min}}, \quad 0 \leq W_t \leq W_{max}, \quad 0 \leq ET_t \leq ET_{max}$$

Where W_t is defined as water applied at day t , R_t is the rainfall at day t which is obtained from weather forecasting, ET_t is evapotranspiration which is calculated from Penman-Monteith equation, D_t is the drainage loss and λ is the cost weighting factor.

iv) Disease Controlling Dynamics

Traditional spray mechanism is kind of fixed internal treatment which farmers apply to the whole field. We propose grid cell precision approach to lower the cost of treatment significantly; the treatment interval is not fixed but preemptive. Pest/disease propagation is

modeled via a spatial SIR (Susceptible-Infected-Recovered) model. The whole field is divided into grid cells to analyze the infection area more effectively and measure the propagation of disease outside that grid cell.

Suppose that:

S_{ij} is proportion of susceptible plants (healthy but vulnerable)

I_{ij} is proportion of infected plants (diseased and contagious)

β is the infection rate of that cell which is obtained from disease sensors, γ_{kl} is the cross grid cell infection rate cell (k,l) to (i,j) which is dependent on the wind or distance and historical spread pattern, and μ is the recovery rate of that plant which is mentioned by the pesticide application.

The initial infection is detected using imaging sensors and DL disease classifiers, then spread is simulated using real time β over a period of 3-7 days and then optimization is performed by solving equation (6 & 7).

$$\min \sum_t (Cost_{pesticide} + \lambda \cdot CropLoss(I_{ij}, t)) \dots \dots (8)$$

B. Decision Agents for Crop Management

The decision agents in our proposed system (Fig. 1) are responsible for making decisions about irrigation, fertilization, and pesticide usage which carry the expenses for farmers and need to be lowered. Hence, decision agents are deployed to optimize resource allocation (e.g., water, fertilizers) and predicting disease dynamics to be pesticide. These agents work by taking IoT sensors data and deep learning agent outputs to enable precise, quantitative management strategies and work in three stages:

- **Stage 1:** Deep learning agents provide values for Crop Growth stage, disease presence in grid cell (i,j)
- **Stage 2:** Real time data from sensors is fetched
- **Stage 3:** Decision agent executes the actions based on the mathematical formulation (Section A) to provide irrigation schedule W_i , schedule of pesticide and fungicide application in a specified grid cell of field.

i) Irrigation Agent

The irrigation agent is designed to ensure optimal irrigation of the wheat crop. An irrigation agent works in coordination with the Weather Forecasting system to determine the water requirements of the crop based on the expected weather conditions. The Irrigation agent takes data from various sensors such as soil moisture sensors, temperature sensors, and humidity sensors, which provide data about the moisture level in the soil and the atmospheric conditions. This data is processed by the module and is used to determine the amount of water required for the crop. The Weather Forecasting system provides data about the expected weather conditions, such as temperature, humidity, and rainfall. This data is used by the Irrigation agent to adjust the irrigation schedule and ensure that the crop receives the required amount of water. The Irrigation agent is also equipped with a scheduling system, which allows farmers to set the irrigation schedule according to their convenience. The module automatically adjusts the schedule based on the weather forecast and the data collected by the sensors through a mathematical model (Irrigation optimization), to ensure crop growth by lowering the irrigation cost. Overall, the Irrigation agent ensures that the wheat crop receives the optimal amount of water, leading to improved yields

and reduced water wastage.

ii) Fertilization and Pasteurization Agents

A smart Fertilization Manager and Pasteurization Guide system help farmers to optimize the use of fertilizers and pesticides in the crop field. It works by analyzing the data collected from various sensors installed in the field and providing recommendations based on the crop's specific needs and environmental conditions.

The Fertilization Manager can suggest the optimal time and quantity of fertilizers to be applied based on the current stage of crop growth and soil conditions. It works based on crop growth modeling to monitor the nutrient levels in the soil and suggest appropriate fertilizers to balance the soil's nutrient content.

The Pasteurization Guide system can help farmers control pest infestation in the crop field. It detects the presence of pests using sensors, and image processing techniques, apply disease controlling dynamics and provides recommendations for the appropriate pesticide to be used. It can also suggest the optimal time and frequency of spraying based on the pest population and the crop's growth stage. A mathematical model suggests the pesticide to be used or not in a field.

Both the Fertilization Manager and Pasteurization Guide can work in coordination with the Irrigation Manager and Weather Forecasting system to provide an integrated solution for crop management.

C. Deep Learning Agents

These agents analyze the information sent by the sensors and give the farmer insights using cutting-edge machine learning methods.

i) Wheat Growth Identification

The dataset used for the experiments is the CGIAR Wheat Growth Stage Challenge dataset [16]. It contains 4,476 RGB images of wheat fields with different growth stages, captured in different locations and under different weather and soil conditions.

Fig. 2 shows dataset contains images of wheat fields where growth stages include Crown Root, Early Vegetative Phase (Tillering), Mid Vegetative Phase, Late Vegetative Phase (Booting), Flowering and Reproductive Phase (Heading), Anthesis, and Ripening and Maturity Phase (Milking). The experiments were conducted using three popular pre-trained models (VGG16, VGG19, and InceptionV3) that were fine-tuned on the CGIAR Wheat Growth Stage Challenge dataset. The models were trained for 20 epochs with a batch size of 32, a learning rate of 0.0001, and the Adam optimizer. Data



Fig. 2. Wheat growth stages – CGIAR dataset.

TABLE II Validation accuracy of fine-tuned models for Wheat Crop Growth

Model	5 Epoch	10 Epoch	15 Epoch	20 Epoch
VGG16	0.7182	0.7948	0.8247	0.8416
VGG19	0.7309	0.8026	0.8311	0.8482
InceptionV3	0.7841	0.8531	0.8723	0.8833

augmentation was applied with random horizontal flip and random rotation (up to 20 degrees) to increase the size of the training set and to prevent overfitting. The results are given in Table II. It showed that all three models achieved high accuracy on the classification task, with InceptionV3 outperforming the other two models. After 20 epochs, InceptionV3 achieved an accuracy of 88.33%, while VGG16 and VGG19 achieved accuracies of 84.16% and 84.82%, respectively.

ii) Wheat Crop Disease Identification

The crop disease identification agent examines the pictures taken by imaging sensors and looks for any indications of disease. In this work, we used transfer learning with the GoogLeNet and InceptionV3 models to predict the occurrence of 12 different types of wheat diseases on the Wheat Disease Detection dataset on GitHub[17].

The data set consists of images of wheat leaves affected by diseases, and the objective is to train a model that can accurately classify these images into one of the 12 classes. We trained models with different combinations of hyperparameters, including learning rate, batch size, and number of epochs, and recorded the training and validation accuracies and losses. The results showed that both models achieved high accuracies, with InceptionV3 slightly outperforming GoogLeNet. Table III presents the outcomes; the best performing model achieved a validation accuracy of 99.31% for InceptionV3 and 99.01% for GoogLeNet, indicating that these models have the potential to be useful tools for wheat disease detection in agriculture.

iii) Wheat Crop Yield Estimation

For training of this deep learning agent, the Wheat Growth and Yield Datasets[18] are used. It is a collection of datasets that includes data on winter wheat growth and yield from different locations in Texas from 1972 to 2013. Table IV presents the outcome comparison of ResNet-18 and VGG19 models on Bushland, Texas Winter Wheat dataset. It shows the loss and accuracy values for each epoch during the training process for the ResNet18 and VGG19 models. It allows for a direct comparison of the two models on this specific dataset. The ResNet-18 model achieved a higher validation accuracy than the smart crop yield prediction system helps farmers to estimate their wheat crop yield accurately.

ResNet-18 outperformed VGG-19 for estimating wheat crop yield from the Texas Winter Wheat dataset, as shown in Table IV. While ResNet-18 attained 87.08% validation accuracy after 10 epochs, VGG-19 scored only 85.10%. In addition, ResNet-18 also had lower validation loss values for both 5 and 10 epochs, which reflects improved generalization and lower overfitting. These findings

TABLE III Comparing InceptionV3 and GoogLeNet, both at Epoch 20 on Wheat Disease Detection

Model		InceptionV3		GoogLeNet	
Hyperparameters		Learning Rate 0.001	Batch Size 32	Learning Rate 0.0001	Batch Size 64
Accuracy	Training	99.45%	96.82%	96.82%	95.32%
	Validation	99.00%	94.67%	94.82%	94.27%
Loss	Training	0.021	0.142	0.151	0.200
	Validation	0.032	0.249	0.205	0.226

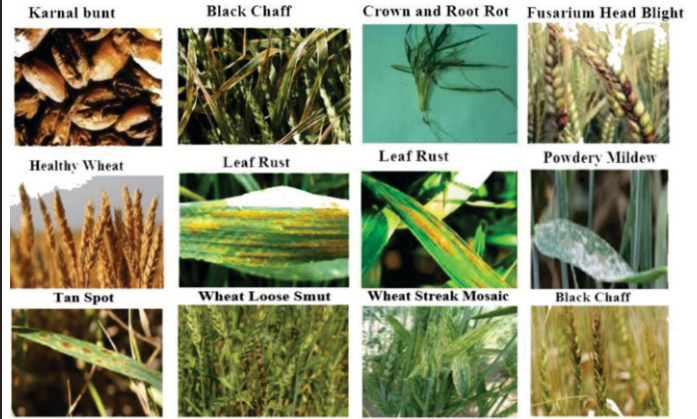


Fig. 3. Classification of 12 wheat diseases using GoogLeNet and InceptionV3

indicate that ResNet-18's residual learning framework is responsible for more efficient feature learning and model convergence, making it a better option for yielding prediction in this scenario.

IV. DISCUSSION

The system is designed to help the farmer make informed decisions about fertilization, irrigation, pest control, and other aspects of crop farming. IoT sensors send data continuously to the system. However, imaging sensors are activated as required. Unlike the existing studies that focus on isolated tasks such as disease detection, yield etc; this study combines sensor fusion, DL diagnostic with 93.31% accuracy for disease detection via InceptionV3 and 88.33% accuracy for growth staging and optimization for decision agents based on mathematical models like SIR, MPC to reduce wastage of resources.

First, a dataset of wheat crop images is collected and labeled to train deep learning models using computer vision techniques. This dataset can be obtained from publicly available sources such as Kaggle or the farmer's field.

Next, the trained model is deployed on a drone camera that can capture high-resolution images of wheat crops. We divide the field into grid cells to deeply analyze the affected area. As the drone flies over the field, it captures images of the crop grid cells and sends them to a cloud-based server for processing. Deep learning models analyze the images to determine the growth stage of the crop and identify any signs of disease.

Decision agents aim to optimize the resources to lower the cost and increase production. These agents use data from deep learning agents and IoT sensors to optimally decide the irrigation, pasteurization, and fertilization schedule. For example, when disease is identified by the system, then decision agent activates the disease control mechanism by considering the affected area and its effect on neighboring grid

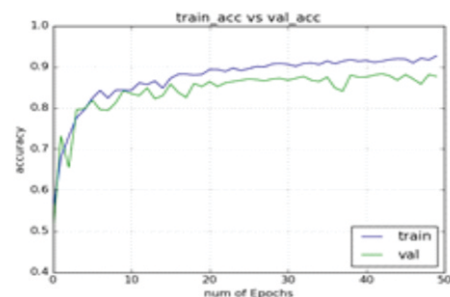


Fig. 4. Model performance on validation set across epochs.

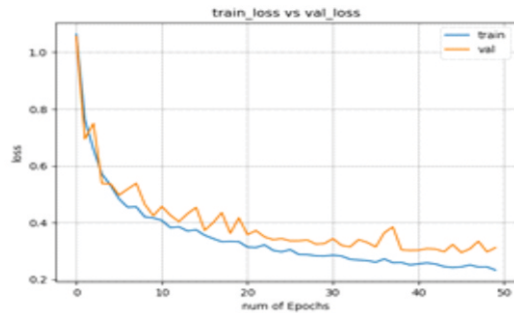


Fig. 5. Final evaluation on test set: accuracy and loss

cells along with other factors like wind, distance, and effectiveness of treatment to optimally choose the treatment of the affected regions. Fertilization agent considers the crop growth stage, nutrients required by the crop and current nutrition level of the field to schedule the fertilization. Irrigation agent not only account for the weather data and soil moisture but also consider crop stage to decide the required amount of water by the crop. This information is then relayed back to the farmer in real-time through a mobile application or web-based dashboard. Based on the results, the farmer can take appropriate actions such as spraying pesticides, fertilizing, or irrigating specific areas of the field to improve crop yield and prevent disease spread.

V. CONSLUTION

We presented a Smart Wheat Crop Management system that collects data on temperature, humidity, and other environmental conditions, and uses computer vision to get crop images. IoT devices are utilized to gather and communicate this data to edge devices and the cloud. Deep learning algorithms are trained to detect crop growth stages, identify any diseases present, and estimate the crop yield. The decision-making agents will operate on live data received from multiple sensors and use deep learning agents for real-time recommendations to farmers on irrigation, fertilization, and the use of agrochemicals like pesticides, fungicides, and herbicides on crops in an optimized way.

TABLE IV Comparison of ResNet-18 and VGG-19 for Wheat Crop Yield Estimation

Model	Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
ResNet 18	5	0.4826	0.8276	0.4449	0.8375
ResNet-18	10	0.3553	0.8757	0.3663	0.8708
VGG19	5	0.5651	0.7989	0.4987	0.8196
VGG19	10	0.4413	0.8403	0.4212	0.8510

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