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OPTIMIZING PLANT GROWTH USING YOLOV11: A DEEP LEARNING APPROACH FOR SUSTAINABLE AGRICULTURE.

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Abstract

In living organisms, plants play a vital role in sustainable life. Plants maintain the food chain, regulate climate change, enhance fertility, provide medicines, support the ecosystem, and meet others' needs. However, environmental challenges such as climate change, air pollution have led to a significant decline in plant populations, resulting in negative impacts on human health, weather patterns, and biodiversity. To address this issue, both Traditional and Non-traditional methods are applied to save the lives of plants. Traditional methods are eco-friendly and low-cost. In contrast, modern methods use advanced technologies to save the plant's life. In recent years, Deep learning models have arisen as a vital tool in agricultural fields for monitoring. Machine learning procedures have shown promise in analyzing plant health, growth, production prediction, and detecting diseases. But these models fail in real-time applications. This study proposes the use of the YOLOv11 model to optimize plant growth. It is a highly accurate model achieving validation accuracy of 92.1%, weighted F-1 Score 91.1% The main aim is to contribute ecological development of agriculture through AI-driven Solutions.

INTRODUCTION

Plants are vital living organisms on Earth. They belong to the kingdom Plantae [1]. There are many species of plants in the world, such as plants, herbs, grasses, shrubs, etc. Most plant yield their food by photosynthesis. It is a progression in which plants use carbon dioxide from the air, sunlight, and water from the soil to produce oxygen and glucose [2]. Plants are multicellular living creatures, contain chlorophyll, a green pigment that absorbs sunlight. Plants cannot move from one place to another like animals [3]. But plants are highly reactive and adaptive to environmental conditions. Plants are vital and play a big role in supporting and maintaining the ecological balance [4]. They produce oxygen in photosynthesis, which is the most important gas for the survival of living organisms, including humans. All food chains are part of plants. Plants give us fruits, vegetables, grains, and other food items [5]. Plants help to adjust the Earth's climate by absorbing carbon dioxide. Plants may also be inspired by the rain pattern and humidity. They reduce soil erosion. They provide us with a healthy ecosystem by increasing the soil fertility [6]. They are also used in health departments, as thousands of medicines such as aspirin, quinine [7], etc. Horticultural green spaces help to reduce stress and increase the quality of life.

The loss of plants, weather due to pollution, climate change, and deforestation pose severe concerns for all the organisms [8]. Plants support various animals as well as microbial life. Many species are becoming extinct because of plant disappearance. They act as a carbon sink. Due to deforestation, global warming is increasing yearly. Deforestation is the main reason for soil erosion, nutrient loss, reduced fertility, and the ability to form [9]. Plant loss decreases the rainfall and increases the risk of droughts and water shortages as plants play a vital role in water cycling [10]. Deforestation increases air pollution and directly affects on respiratory system. So it's essential to save the plants because saving plants means saving the future. As human beings, we have to save them for a clean and healthy environment [11]. There are many ways and producers to save the plants.

Firstly, choosing the right plant is an essential step because the local climate, soil type may impact the plant's growth. Secondly, the soil should be rich in nutrients and have good drainage. Natural fertilizers can be added if required to improve the fertility of the soil. Thirdly, maintain the proper space between the plants to ensure the healthy growth of the plants. Fourthly, regularly give water to the plants, but over-watering is not good. The watering amount depends on the type of water, as rice paddy requires more water. Fifthly, Sunlight is very important for the growth of plants because they produce their food in the presence of light. So, place the plants in locations where they can get light for at least 6 hours. Sixthly, remove the weeds from the plants, as weeds can compete for the nutrients. Use natural pest repellents to deter harmful insects. Seventhly, regularly monitor the plant for signs of disease or nutrient deficiency [12] [13] [14]. The number of growth stages involved in the plant growth is given in

Figure 1 below

Figure 1:Plant Growth

Both traditional and non-traditional methods have been used to defend the plant's life [15]. **Traditional methods** are old methods of saving plants. People have used them for many years. These methods are eco-friendly and inexpensive. Farmers used animal dung, compost, and leaves to fertilize the soil, thereby saving plant life [16]. They used herbal repellents instead of chemical repellents. They practice companion planting to control the pests. Changing crops each season helps to maintain the earth's fertility. This method improves plant growth naturally. **Non-traditional (Modern) methods** used technology, global policy, and research to protect the plant's life. Tissue culture involves growing plants from cells in a laboratory. Smart irrigation involves drip irrigation or automatic watering systems to save water and to keep plants healthy [17]. Satellite monitoring is used to monitor the forest cover, plant growth, and illegal logging [18]. Genetic engineering is used to modify the genes to make them nutrient-rich [19].

Recent advances in deep learning and computer vision have enabled high-impact applications across medical imaging, urban mobility, and security systems. Convolutional neural networks (CNNs) have proven particularly effective in medical image analysis, such as in mobile applications for skin disease classification with user privacy safeguards [20], and innovative fungal disease detection systems [21]. In broader computer vision applications, CNN-based frameworks have also been applied to the automated classification of ammunition types [22] and general image classification tasks [23], and autonomous road sign detection [24]. These studies demonstrate the versatility and accuracy of deep learning approaches in both healthcare and security domains.

Beyond healthcare, smart city innovations have greatly benefited from the integration of IoT, computer vision, and deep learning. For example, autonomous parking-lot detection systems using multi-sensor fusion T. Alyas et al. and IoT-enabled intelligent urban parking systems with transfer learning [25] offer scalable mobility solutions. Additionally, machine learning has been employed to mitigate road traffic congestion through adaptive control systems [26]. In parallel, the field of cybersecurity has seen focused efforts such as ransomware behavior analysis and surveys [27]. These works collectively signify a shift towards AI-powered automation in infrastructure, security, and urban management, underpinned by deep learning's robustness and adaptability.

Recent advancements in AI are transforming agriculture by automating tasks such as growth stage, yield production, and disease analysis from images. CNNs [28], DCNN [29], RNNs, Faster-RNN [30], ANN [31], and GANs [32], but are not good for real-time applications. The present study uses a Deep Learning Model, YOLO [33], for the monitoring and proper growth of the plants. The goal is to propose a system that can monitor and optimize the proper growth of plants, preserving accuracy, minimizing the cost, and time.

Methodology:

Model Construction and Working:

The proposed model consists of three parts such as IoT is used to take the picture of plants as input and send it to the Detection unit, before going to the detection unit augmentation is done on the image data. The detection unit detects the growth of the plant step by step on the basis of features extracted from the image data. The third one is the output unit; it is used to display the plant growth. The complete plant growth system is given below in Figure 2.

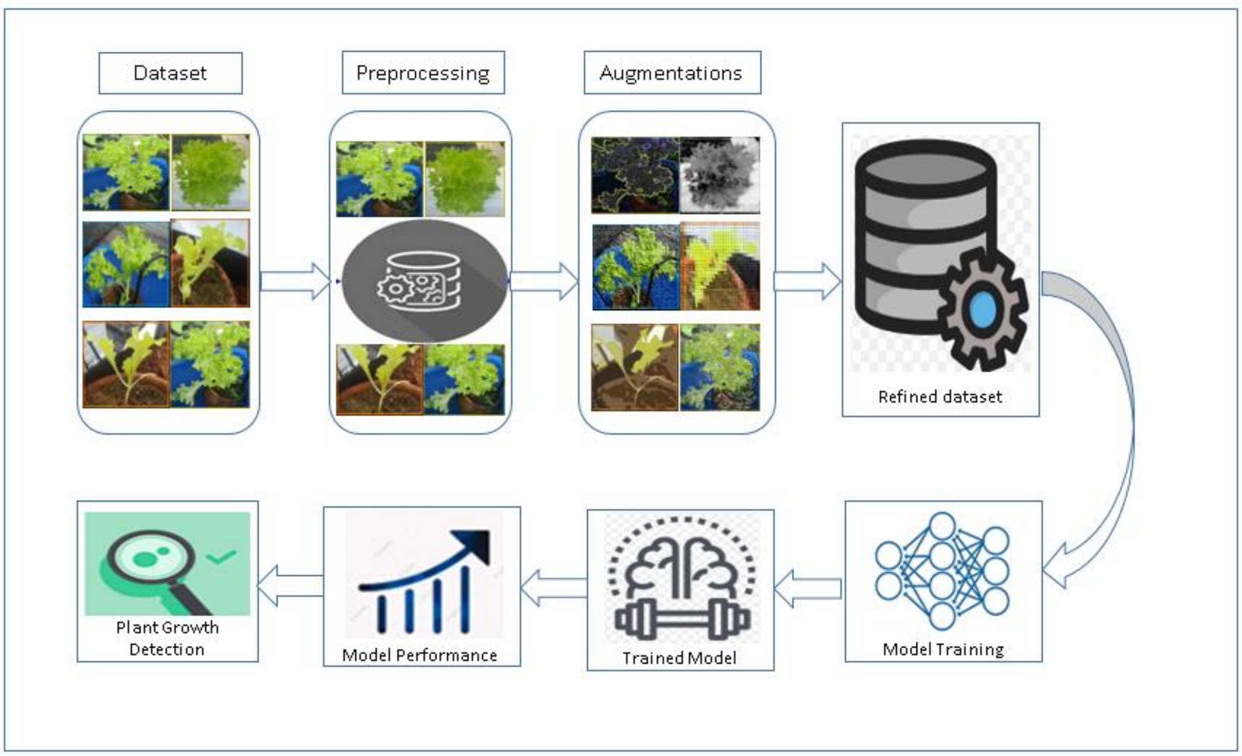


Figure 2: Proposed Model

Working of the Model:

The process starts with a dataset, which consists of images or sensor readings. For diagnostic purposes, the data undergoes several preprocessing steps. An Augmentation technique is also applied, which improves the diversity of the photos and the model's performance. The refined dataset is then used to train the model, where algorithms learn the pattern. The model performance is calculated to ensure the reliability and accuracy of the model. Finally, the trained model is deployed in the real world for the detection of plant growth.

Dataset and Resource:

Dataset (Lettuce growth stage detection) is chosen from well know and authentic website "Roboflow" by ensuring the data validity and authenticity. Data is already resized and auto-oriented. Image sized stretched to 420*420. The dataset is divided into Training 70%, Testing 20% and Validation 10%. Figure 3 below shows the splitting of data used in the model training, testing, and validation.

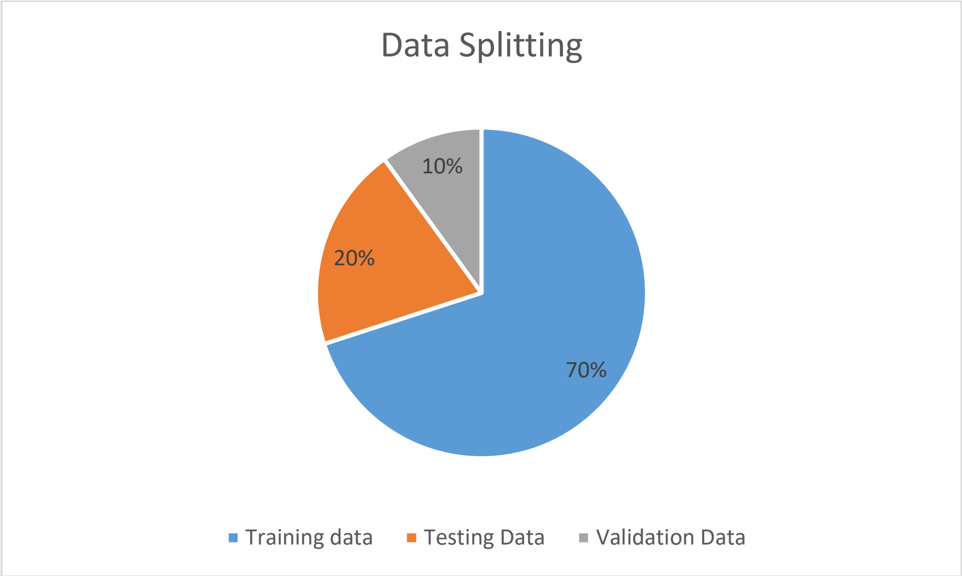


Figure 3:Data Splitting

Total No. of Classes Vs Instances:

The graph given in **Figure 4** represents how many instances exist for each class in the selected dataset.

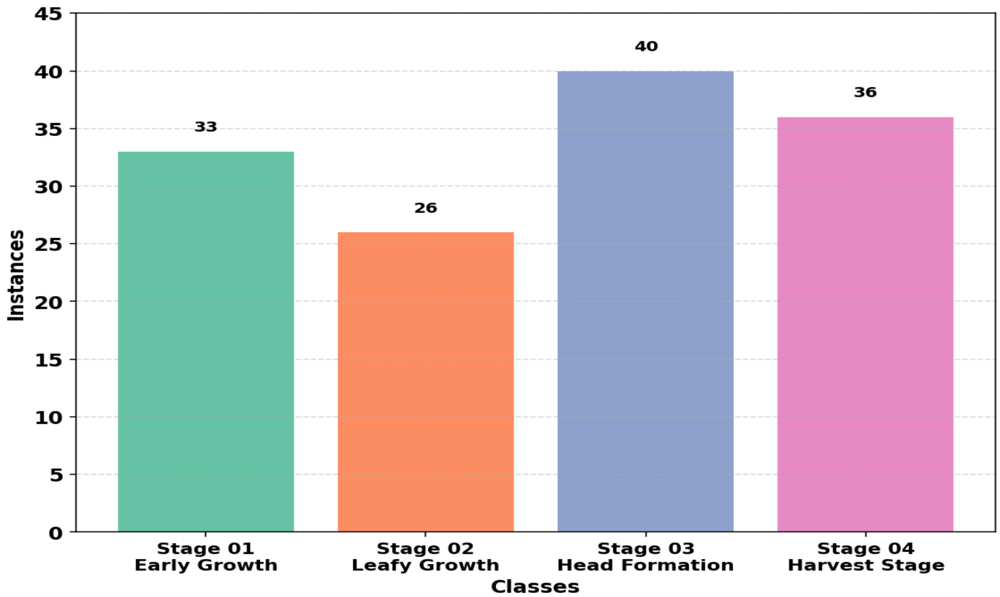


Figure 4: Instances vs Classes

Performance Metrics:

These metrics are used to check the efficiency of the models. Table No. 1 below shows the performance metrics.

Table 1: Performance metrics

Matric	Formula
Precision	$\frac{tp}{tP + fp}$
Recall	$\frac{tp}{tp + fn}$
Accuracy	$\frac{tp + tn}{tp + tn + fp + fn}$
F1-Score	$2 * \frac{P * R}{P + R}$
FNR	$\frac{fP + fn}{tp + tn + fp + fn}$
TPR	$\frac{tp}{tp + fn}$
TNR	$\frac{tn}{tn + fp}$

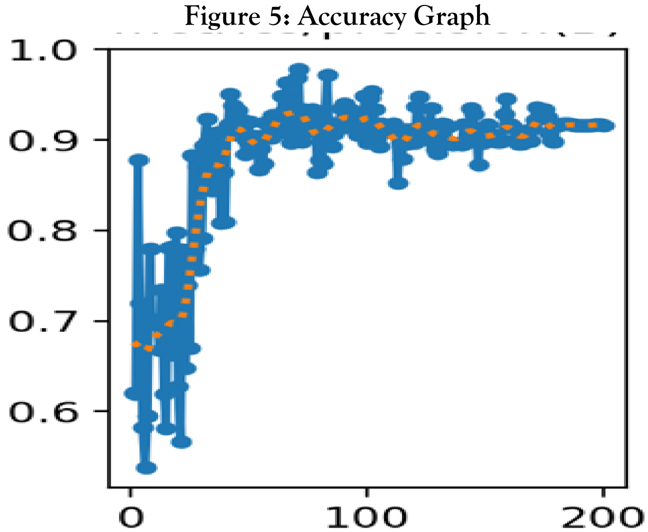
Confusion Metrix:
A Confusion Matrix is used to calculate the performance of a classification model. We compare the predicted class with the actual class. The confusion metric of the model is given below in Table 2, below.

Table 2:Confusion Metric

		Predicted Values				
	N=1871	**Stage 01**	**Stage 02**	**Stage 03**	**Stage 04**	**Total**
True Values	**Stage 01**	6	0	0	0	**6**
	Stage 02	1	6	0	0	**7**
	Stage 03	0	1	10	0	**11**
	Stage 04	0	0	1	13	**14**
	Total	**7**	**7**	**11**	**13**	**38**

Accuracy Graph
The graph accuracy is the training accuracy that represents how the accuracy of the model changes over time during training. The below graph shows the accuracy progression over training epochs. On the X-axis, the No of epochs is 0 to ˜ 200, while on the Y-axis, accuracy values range from ˜ 0.55 to 0.10. The blue dotted line shows accuracy per epoch. The orange dotted line shows the Smooth trend of accuracy. The accuracy graph is given in the Figure below.

Figure 5: Accuracy Graph



Accuracy-Y-axis
Epochs- X-axis

Precision Graph

The precession graph is used to measure the performance of the model. It also evaluates the performance of the object detection model. The curve shows how YOLOv11 detects different stages of plant growth. There are four stages of plant growth Such as Stage-01 -Early growth, Stage-02 -Leafy Growth, Stage-03 -Head Formation, and Stage-04 – Harvest. The model performance is best at stage-04, that is harvest stage. At stage 04, the model performed best with 0.995, while the lowest stage-02 leafy stage with 0.960. The overall Mean Average Precision (mAP) is 0.5. The excellent accuracy across all classes is 0.97 at Stage-01 (Early growth) and Stage-03 (Head Formation). The precision and Recall graph is given in Figure 6 below.

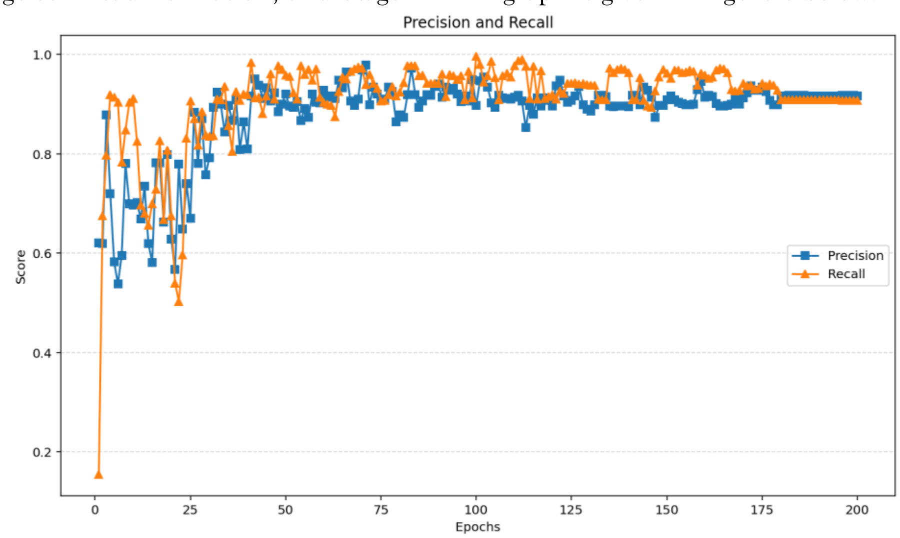


Figure 6: Precision and Recall Graph

F-1 Graph:

The F1-Confidence Curve reveals how the model's F1-score deviates with dissimilar confidence thresholds for noticing numerous crop growth stages. Most phases demonstrate high performance between 0.1 and 0.85 confidence, with the strongest overall F1-score (~0.799) attained at a threshold of 0.91. After this PowerPoint, performance descends abruptly due to reduced recall. Between all stages, the Harvest Stage achieves best reliably. This investigation supports choosing the optimal confidence threshold for accurate and balanced calculations in real-world agricultural applications. Figure 7 shows the F-1 confidence curve below.

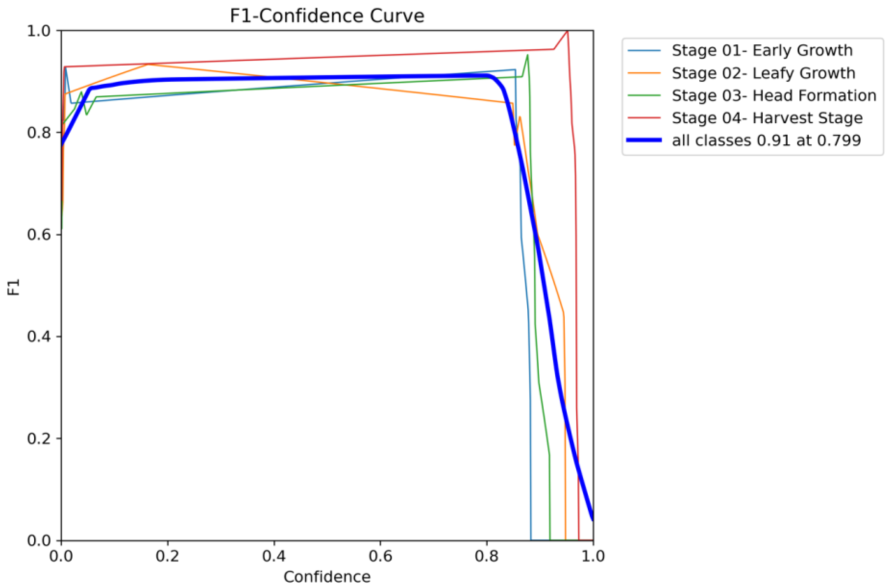


Figure 7;F-1 Score Graph

Recall- graph:

The Recall-Confidence Curve demonstrates that the model sustains high recall (above 0.85) through all crop growth stages. The maximum overall recall (~0.98) is attained at a very low confidence threshold (0.000), representing that the model can detect almost all appropriate occurrences. Conversely, recall drips abruptly as confidence rises, particularly beyond 0.85. The Harvest Stage demonstrates the strongest recall performance overall. This examination recommends that using a lower confidence threshold is operative for maximizing recall in agricultural monitoring tasks. The Recall curve is shown below in Figure 8.

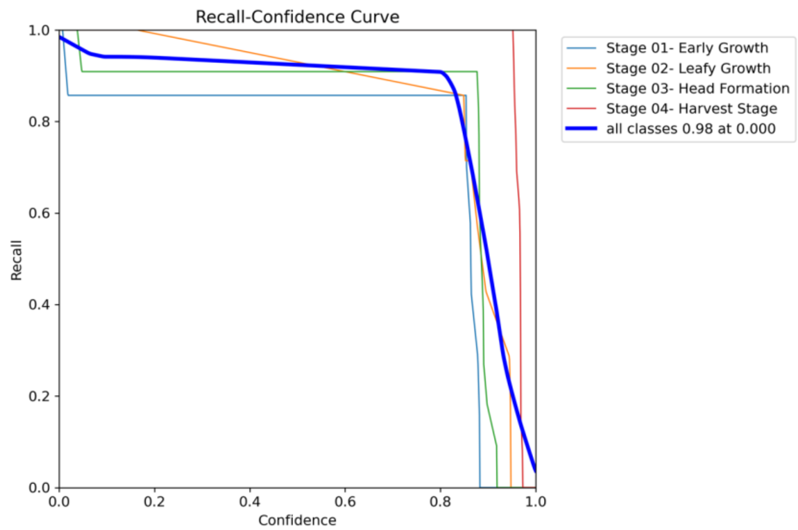


Figure 8:Recall Graph

Precision vs Validation Loss Graph:

The graph shows that the model quickly reduces both precision and validation loss. It shows that the model is learning steadily, and abrupt changes show the overfitting of the model. Figure 9 shows the precision-validation graph of the model.

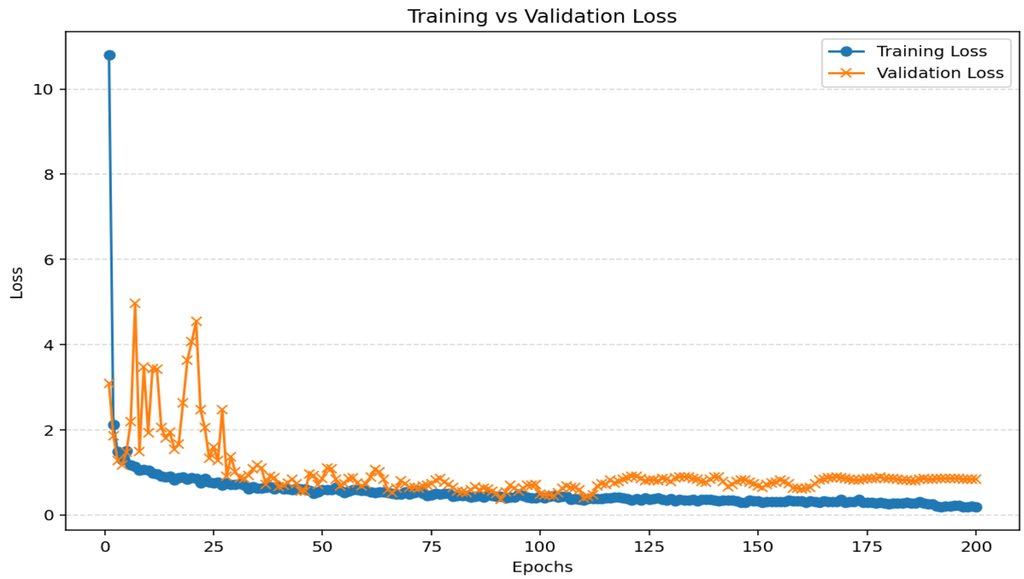


Figure 9:Precision vs Validation Loss

Model Performance:

The overall performance of the system is shown in Figure 10 below.

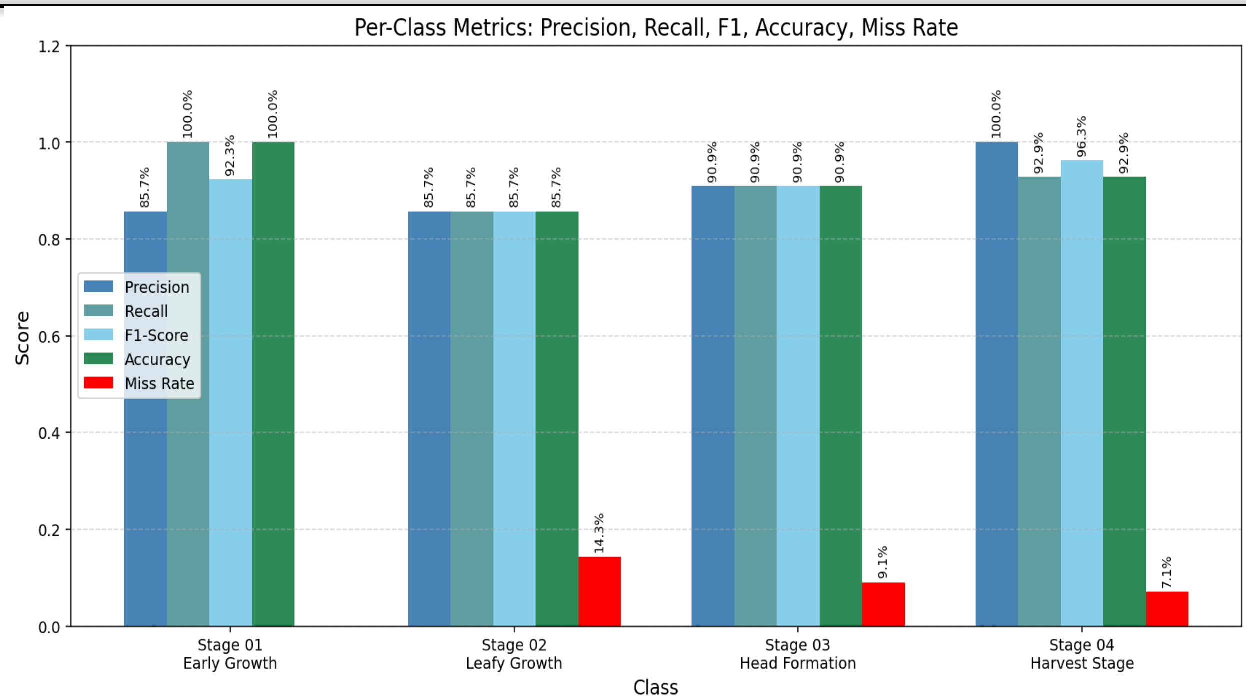


Figure 10: Performance Metrics

Comparison Results using Different Deep Learning Models for Plant Growth:
Table No. 3 represents the performance metrics results of different models.

Table 3:Comparison Table

Micro average					Macro average			
Performance Metrics	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
InceptionV3 [34]	0.875	0.750	0.750	0.750	0.875	0.734	0.734	0.733
DesneNet [34]	0.858	0.717	0.717	0.717	0.858	0.704	0.695	0.702
ResNet [34]	0.881	0.762	0.762	0.762	0.881	0.750	0.747	0.747
Human expert [34]	0.772	0.543	0.543	0.543	0.772	0.537	0.54	0.537
Our Proposed Model Yolov11	**0.897**	**0.897**	**0.897**	**0.897**	**0.906**	**0.906**	**0.924**	**0.913**

Conclusion:
For environmental stability, food, providing medicine, preparing, and ecosystem-sustaining plants play a vital role. Due to quick changes in the environmental climate, pollution and other environmental factors are alarming decline in the plant population. This crisis poses a serious risk to human health and food security. Traditional methods fall short in scalability and Real-time monitoring, while the advancement of modern technologies, such as deep learning, provides new ways to protect plant health with high efficiency and precision. Machine Learning Models have shown success in growth analysis, yield prediction, and plant disease detection. However, there are limitations in implementing vigorously in an agricultural environment, including real-time performance restrictions. TO overcome this gap, we apply the

YOLO11 model that provides a solution for real-time plant growth optimization. The reported validation **accuracy is 92.1% and weighted F-1Score 91.1%.** YOLOv11 presents high precision for plant monitoring in a real-time agriculture environment. This research contributes considerable development and improved outcomes in agriculture. It helps in achieving global food security. Future advancements in deep learning and optimization of models will continue that enhance the capabilities of integrating with technology for environmental protection.

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