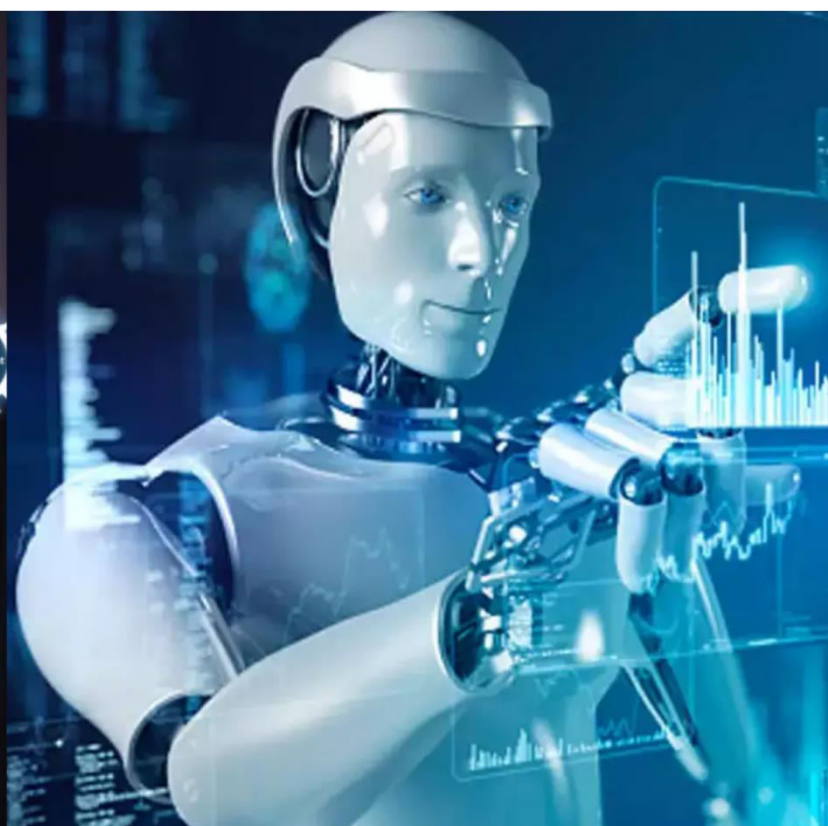




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Plant Growth Prediction using CNN

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ABSTRACT: Machine learning (ML), when integrated with image analysis and plant growth assessment tools, is transforming farming entirely. The advanced technology, which integrates image analysis and machine learning, allows for precise prediction of plant growth patterns. The work presented helps the novice farmer by directing them to sow suitable crops by use of machine learning, one of the advanced technologies, in crop predictions. Naive Bayes, a supervised learning algorithm will carry it out. With respect to this science, crop seed data are accumulated with proper parameters, like temperature, humidity, and moisture content to make sure that agriculture blooms. As software, this mobile application is being developed for Android. The application allows them to fill in temperature; the location of the user is picked up automatically, and then the prediction starts.

KEYWORDS: Plant Growth, Machine Learning, Image Processing, Advance CNN.

I. INTRODUCTION

From the beginning of civilization and human existence, agriculture is believed to have been one of the major suppliers of human needs. All these sub-castes are major in agriculture for many reasons: mostly representing food, which forms a surplus for other people, but still depends really on color, taste, and so on. The timing of traditional naked-eye observations on healthy cropping suggested that the use of chemicals in animal feed and crop establishment not only for diversity maintenance was prohibited. But by nature, the weather changes tend to go against elemental components responsible for causing hardship and threats to the safety of food security. Also, in spite of the agricultural GDP steadily on the path of decline-where in 2005 it was 17.2%, in 2012 it had dwindled to 11.1%, and by 2018 it fell to 5%; while the first quarterly forhiteen year, 2109-2020, reached as low as 2%. Roughly 80% of farmers are in the rural sector, if the revenue from crop production shrinks, their mode of life will be changed by farms at the industrial level. Image processing techniques have been applied along with machine learning in this current study to predict the growth and development of plants. The project involves taking high-resolution images of plants at all different stages of growth to extract the relevant growth data from them. AI-backed platforms can keep a tab on large data sets in real time, giving insights into crop vigor, moisture levels, and soil situations. Farmers could cut waste and minimize their environmental footprint by deploying water, herbicides, and fertilizers only when they are required. Crop breeding in case of ML would simplify the problem and processes

A. Problem Definition:

They include environmental conditions (temperature, humidity, soil moisture); the type of the plant; and other stressors (diseases, pests). Accurate growth modeling is vital for improving agriculture, crop yield, and various aspects of sustainable farming. With traditional methods of punishing plant growth being time-consuming and subject to many forms of errors, they impede an accurate decision-making process in regard to irrigation, fertilization, and pest management

Into this new era of machine learning and other deep learning algorithms comes a very promising opportunity to invoke automatic models for the prediction of plant growth. In particular, Convolutional Neural Networks, because they are very powerful techniques for the analysis of visual data, could take plant images over time and predict their future growth path. The training of a CNN model on most cases for plant images and corresponding growth data would allow the model to understand underlying patterns that relate to plant health, developmental phases, and growth rate in real time.

B. Scope:

- Modern farming practices are going to be more smart and effective thanks to new technologies such as machine learning and image processing.
- Farmers will be able to base their sustainable practices on precise estimates of plant growth based on long-term viability for the agricultural practices they implement which will decrease the impact on the environment.

II. RELATED WORK

In 2023, Anand SS et al. [1] explained that plant diseases pose a significant challenge to India's agriculture due to limited understanding of disease markers and remedies. They emphasize the potential of deep learning, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for improving disease detection. The study explores the application of Machine Learning (ML) algorithms like KNN, Logistic Regression, Random Forest, Naïve Bayes, Decision Trees, and Support Vector Machines (SVM) on crop image datasets. A CNN-based system, combined with ML-driven soil analysis, recommends optimal crops for planting. The superiority of Support Vector Classifier (SVC) is highlighted through classifier comparison. The integration of pre-trained models (VGG16, InceptionV3, ResNet152) and IoT technologies further enhances disease and yield prediction, offering solutions to boost agricultural efficiency and global food security.

In 2023, Ogawa and Kumaki [2] explained that despite over 50% of India's land being fertile, agricultural production does not meet expectations, largely due to plant diseases that impact food yield. This study proposes a multilayered convolutional neural network (CNN) algorithm to predict plant diseases, suggest appropriate fertilizers, and recommend pesticides, enabling early intervention for farmers. Using datasets from GitHub, the CNN classifies diseased plant leaves based on real-time images captured with high-resolution cameras, comparing them to healthy and unhealthy datasets. The system then provides accurate disease predictions and displays results to guide actions. This approach demonstrates how modern neural networks, when trained with optimal datasets, can significantly improve agricultural outcomes by offering timely, data driven insights.

In 2024, Akbar et al. [3] explained that while agriculture in plant factories has gained attention, it remains less profitable than traditional farming. To address this, optimizing the cultivation schedule is key to enhancing profitability. This study presents a method for plant growth prediction in plant factories using microcomputers and sensors to measure environmental conditions. Long Short-Term Memory (LSTM) algorithms are used to predict the size and weight of vegetables. Experimental results show that the best accuracy is achieved at 50 epochs, with MSE and MAE values of 0.077348 and 0.187984 for size prediction. However, weight prediction yielded lower accuracy, with an MSE of 0.165420 and a coefficient of determination exceeding -2. The results demonstrate effective size prediction, though further improvement is needed for weight accuracy. Future research will focus on enhancing the precision of weight predictions to improve overall plant growth modelling in smart greenhouse environments.

In 2022, Poornima et al. [4] addressed the rising global challenges of food security and resource sustainability by exploring the transformative role of deep learning and computer vision in agriculture. Their paper reviews recent advancements in deep learning-enabled computer vision techniques for greenhouse environments, analyzing over 100 studies from 2020 onwards that focus on growth monitoring, disease detection, and yield estimation. The research evaluates the datasets, models, and performance outcomes reported in the literature, while highlighting key challenges such as model adaptability, insufficient labeled data, and computational limitations. Tables and figures illustrate real-world applications, with future trends discussed to guide researchers in this niche domain. The review fills a critical gap by offering a focused analysis specifically on greenhouse environments, emphasizing the potential of smart greenhouse farming driven by AI technologies.

In 2020, et al. Sergey Nesteruk[5] have researched Due to resource scarcity, climate change, and rising global food consumption, novel agricultural technologies are essential. Using sensor technologies, machine learning, and data analytics, "intelligent embedded sensing" is a unique approach to plant growth prediction that tracks and predicts plant development in real-time. Sensors are used to continuously collect vital data regarding environmental elements in

agricultural settings, such as temperature, light, soil moisture, and nutrient levels. These data streams give farmers pertinent information and enable precise plant growth prediction using potent predictive algorithms.

In 2021, et al.mamunur rashid [6] have explained Crop yield prediction is a critical part of modern agriculture, providing insights that improve decision-making, optimize resource use, and ensure food security. Machine Learning (ML) approaches, which evaluate massive amounts of data on soil, environment, and management characteristics, have emerged as particularly powerful tools for predicting agricultural output. This detailed review examines many machine learning algorithms for predicting crop yields, with a particular emphasis on palm oil yield prediction because it is a major agricultural product with significant economic implications. The research examines regression algorithms, decision trees, support vector machines (SVM), and deep learning networks to demonstrate the advantages and disadvantages of classical machine learning (ML) models for yield forecasting.

In 2023, et al.Sariga Sankaran[7] have researched Early detection and accurate prediction of plant leaf diseases are crucial for sustaining crop production and preventing large-scale agricultural losses. With the increased use of technology in farming, new approaches such as Machine Learning (ML) and Image Processing have the potential to alter modern agriculture. This study looks into cutting-edge approaches for identifying and predicting plant leaf diseases utilizing photos captured by embedded sensors, drones, and mobile devices. These systems use machine learning techniques such as Convolutional Neural Networks (CNNs) to detect and predict diseases based on leaf texture, colour, and shape.

In 2022 et al. Santosh Kumar [8] have researched Artificial intelligence (AI) in agriculture has opened up new possibilities for precision farming, with plant growth monitoring systems emerging as critical instruments for optimizing crop management. This article discusses an artificial intelligence-powered Plant Development Monitoring System that uses machine learning algorithms, image processing techniques, and sensor data to track and predict plant growth patterns in real time. The system gives information about the plant's health and growth stages by continuously collecting data on environmental factors such as temperature, humidity, soil moisture, and light intensity, as well as photographing plant morphology.

In 2023,et al. Masahiro Ogawa[9] have reseaeched The growing desire for efficient and sustainable food production has led to the establishment of plant factories, which are controlled indoor environments that encourage plant growth. Accurate plant growth prediction under these conditions is crucial for resource management and yield enhancement. This research describes a plant growth prediction methodology based on the Long Short-Term Memory (LSTM) method, a type of recurrent neural network (RNN) that is effective with time series data. By analyzing previous data on environmental variables including as light, temperature, humidity, and nutrient levels, the LSTM-based model forecasts future growth trends in real time.

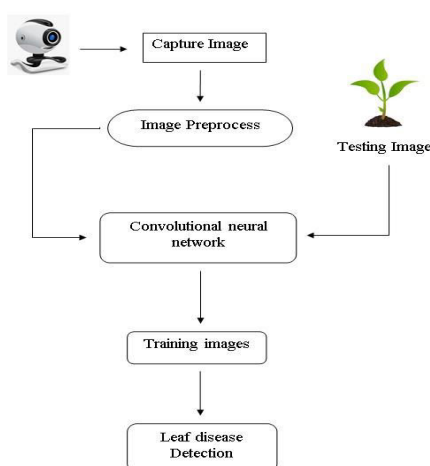


Fig.1. Workflow

In 2021, Srinidhi et al. [10] explained that plant diseases have inflicted significant suffering worldwide, causing an estimated annual yield loss of 14%. Plant pathology aims to enhance the survival of plants under unfavorable environmental conditions caused by pathogens. Factors such as temperature, pH, humidity, and moisture contribute to the development of plant diseases. Misdiagnosis can lead to economic losses, environmental imbalances, and the emergence of resistant pathogen strains. Current diagnosis methods are time-consuming, costly, and reliant on human scouting. This project proposes an automated disease segmentation and diagnosis system using Deep Convolutional Neural Networks (CNNs), specifically EfficientNet and DenseNet, to detect and classify apple plant diseases from leaf images into four categories: "healthy," "scab," "rust," and "multiple diseases." The apple leaf disease dataset is enhanced through data augmentation and image annotation techniques, including Canny Edge Detection, Blurring, and Flipping. The models achieve high accuracy rates of 99.8% and 99.75% for EfficientNetB7 and DenseNet, respectively, addressing the limitations of traditional convolutional neural networks.

III. METHODOLOGY

Convolutional neural networks (CNNs) that use techniques outside of their basic architecture to enhance performance and solve particular problems are known as advanced CNNs. Sometimes these developments call for adjustments to regularization plans, training regimens, or network architecture.

Convolutional Neural Network is the acronym for CNN. For computer vision and image recognition applications, this kind of deep learning technique is frequently employed. Convolutional, pooling, and fully connected layers in a CNN are designed to automatically and hierarchically learn features from input images. CNNs are therefore well-suited for tasks like object detection, picture classification, and facial recognition because they can efficiently capture spatial and hierarchical patterns in images. CNNs have been widely used in many applications and have revolutionised the field of computer vision.

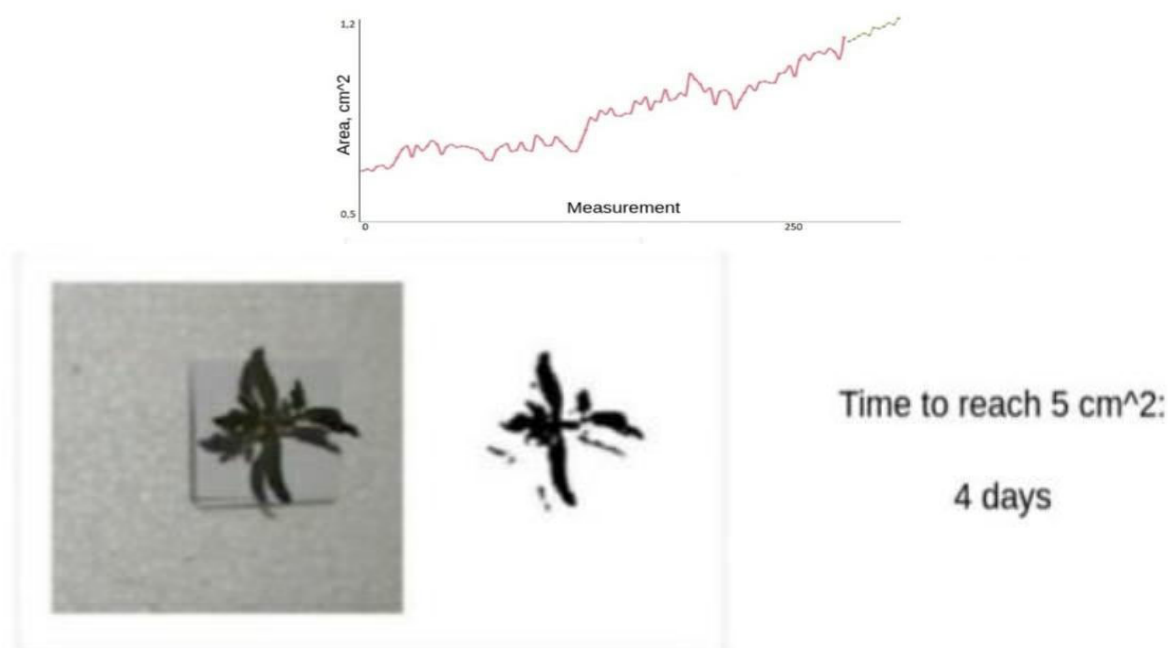


Fig.2. Monitoring System user interface

Advanced CNNs incorporate various enhancements beyond the basic architecture to improve performance and address specific challenges. Some of the sophisticated architectures include ResNet, which introduces skip connections to mitigate the vanishing gradient problem and enables deeper networks. DenseNet further optimizes feature reuse by connecting each layer to all subsequent layers, reducing redundancy and improving efficiency. In contrast, EfficientNet balances depth, width, and resolution scaling for fewer resources and the optimum performance.

Regularization techniques prevent over fitting and improve generalization. Dropout randomly deactivates neurons during training, which prevents the network from relying too heavily on certain features. Batch normalization normalizes activations across batches, which makes training more stable and faster, and L2 regularization, or weight decay, penalizes large weights to prevent over fitting.

CNNs consist of several layers that work together to extract features from input images. Here's a breakdown of the different layers in a CNN:

1. **Input Layer:** The first step is to define the input layer, which takes in the image data.
2. **Convolutional Layer:** This layer uses convolutional techniques to process the input. It uses filters, or kernels, that move across the image to recognize features like edges, textures, and patterns in the input image. What's left over are feature maps.
3. **Pooling Layer:** This layer helps reduce the number of parameters and calculations in the network by reducing the spatial dimensions of the feature maps. Two common methods for pooling are average and maximal pooling.
4. **Flattening:** The pooled feature maps are then flattened into a 1D vector to create space for the fully connected layers
5. **Fully Connected Layer:** There are one or more fully linked layers that are connected to the flattened vector in this layer.
6. **Output Layer:** The output is generated by the last layer. It typically outputs the probabilities for each class using a softmax activation function for classification tasks.

IV. SYSTEM ARCHITECTURE

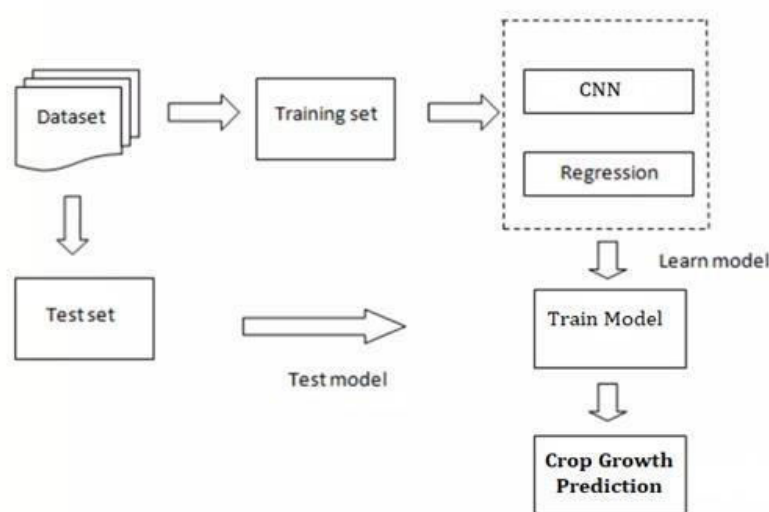


Fig.3: System Architecture

1. **Dataset:** It typically consists of images of crops tagged with relevant growth characteristics, such as height and weight, at different phases of their growth.
2. **Training set:** A portion of the dataset used to train the machine learning algorithm. The input photos and the labels that go with them are matched, and the model finds patterns and relationships between them.

3. CNN (Convolutional Neural Network): A particular kind of deep learning model intended to process image data. It makes advantage of elements that are essential for forecasting crop growth from the input photographs, including as forms, edges, and textures.
4. Train Model: The model learns from the training set and improves the accuracy of its predictions throughout this actual training phase.
5. Test Model: This is the process of evaluating the model's performance on the test set.
6. Crop Growth Prediction: The final output of the model, representing the predicted crop growth based on the input images.

V. CONCLUSION

The integration of machine learning and image processing in agriculture enables farmers to make data-driven decisions, optimize resource allocation, and improve crop health. These technologies facilitate early disease detection by analyzing plant images to identify symptoms that may not be visible to the human eye. Convolutional Neural Networks (CNNs) and other deep learning models can classify plant diseases with high accuracy, allowing for timely intervention and reducing crop losses.

Other than disease detection, growth monitoring and yield prediction also benefit from such advancements. The machine learning models analyze plant images over time to assess growth rates, nutrient deficiencies, and environmental stress factors. Using historical data and real-time imaging, the models provide insights into expected yields for farmers, allowing them to better plan and distribute resources.

Another huge outcome of joining image processing with AI is precision farming. Using drones and satellite imagery, it scans large agricultural fields and captures images that are processed by machine learning models to determine soil health, water distribution, and crop density. This helps farmers optimize their irrigation schedules and find better ways to apply fertilizers and reduce total waste so as to have sustainability.

Challenges are still there. The high cost of investment required for AI-driven tools and imaging technology can deter small-scale farmers. Also, the data security and privacy concerns arise since humongous farm data is being collected and stored. Internet connectivity in rural areas is also limiting the real-time processing and cloud-based analytics. However, the scope of innovation and growth in agriculture is enormous. The advancement of edge computing enables the processing of data locally, significantly reducing the need for internet connectivity. Increasing government and private sector support for smart farm solutions will accelerate the availability of technologies for smart farming. When these all come together, precision agriculture will ensure that produce gets to the table with more yields, decreased environmental effects, and greater food security, thereby positioning technology as the driving force behind modernizing agriculture.

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