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A SMART HYDROPHONIC PLANT DISEASE DETECTION SYSTEM USING CNN

GowthamV[1],GuhanNS[2],BalasubramanianM[3],GangaduraiE[4]

[1,2,3]Students,and[4]Faculty
Dept. of Electronics and
CommunicationEngineering,VelammalE
ngineeringCollege,Chennai,
India.gangadurai@velammal.edu.in

Abstract: *A considerable portion of India's population actively participates in agriculture, serving as a crucial pillar of the nation. Despite its fundamental role, the agricultural sector encounters various challenges, including limited land availability, extensive use of harmful pesticides and chemicals, and a growing consumer preference for high-quality, chemical freefood.SoOursolutionaddressesthesechallengesbyembracingorganicfarmingmethods,enablingmeticulous cultivation in various settings, including indoor spaces like rooms, balconies, and terraces. The utilization of a hydroponic system eradicates the dependence on soil by utilizing nutrient-rich water for efficient plant cultivation, free from soil contamination. Over the past few years, there has been an increasing interest among researchers in automating hydroponic systems to improve operational efficiency and decrease the need for manual labor in agriculture. This endeavor seeks not only to improve overall profits but also to increase the yield of agricultural produce. Yet, the ultimate triumph of an automated hydroponic system depends on its capacity to accurately identify and tackle crucial issues like plant diseases, nutrient deficiencies, and inadequate water supply. Overlooking the identification and resolution of these challenges may result in significant crop losses and financial setbacks, emphasizing the urgent requirement for advanced technological solutions. This paper presents a cutting-edge Internet of Things (IOT)-driven machine learning system tailored for the identification of plant diseases, utilizing an advanced Deep Convolution Neural Network(DCNN).*

Keywords: *Agriculture, organic farming, hydroponic system, soil contamination, automation, nutrient deficiencies, water supply, IOT, machine learning, Deep Convolution Neural Network (DCNN), plant diseases, Indian agriculture*

1. INTRODUCTION:

In India, farmers have the privilege of cultivating a diverse array of vegetation. However, various environmental pathogens can significantly impact both plants and soil, leading to a decline in crop yield. Effectively managing agriculture requires the crucial identification of plant diseases, with leaves serving as primary indicators of affliction. The distinctive colored spots and patterns on leaves provide valuable cues for disease detection in the current approach, which, unlike previous methods, has no adverse effects on the environment or crop quality. Historically, the reliance for the detection of plant leaf diseases has been on manual visual observation, with consideration given to variables such as weather conditions and seasonal variations. In the context of India, being predominantly an agrarian nation with around 80% of its population depending on agriculture, the impact of plant leaf diseases is substantial, resulting in a reduction in both the quantity and quality of agricultural yields. The analysis of visually discernible patterns on plant leaves is deemed imperative for a comprehensive understanding of plant health and the formulation of strategies to address diseases, thereby ensuring optimal cultivation outcomes. This approach was both labor-intensive and time-consuming. In contrast, the novel method utilizes technology to simplify the process, providing a more efficient and effective way to identify

The challenge presented by plant leaf diseases leads to substantial reductions and losses in both the quality and quantity of agricultural products. Agricultural yields, heavily relied upon by a significant portion of the burgeoning population in developing countries, are impacted. However, the demanding endeavor of cultivating plants for optimal yield and premium quality products involves technical intricacies. A revolutionary method of plant cultivation without soil is introduced by hydroponics. In this innovative approach, plants are arranged in rows or on trellises, resembling traditional gardens, but their roots receive sustenance from water instead of soil. It is crucial to emphasize that soil provides structure, not the actual nutrients for plant roots. Nutrients are derived from various substances within the soil, including compost, decomposed plant waste, or fertilizers. Hydroponically grown plants demonstrate accelerated growth and enhanced health compared to their soil-bound counterparts. They thrive without the need to contend with soil-borne diseases, receiving a continuous supply of all necessary nutrients and water directly to their roots. With fully automated growing tables tailored for home gardeners, hydroponics simplifies the cultivation process, proving to be more straightforward than traditional soil-based cultivation. The essence of hydroponics lies in its simplicity – plants require food, water, and air. Breaking down the essentials, it becomes apparent that providing plants precisely what they need is uncomplicated. Hydroponics, essentially the science of cultivating plants without soil, offers an efficient and streamlined approach to plant growth .Plant diseases come in various forms, classified by their severity, including bacterial, viral and fungal diseases. When a pathogen in filtrates your plants, observable signs include the development of galls, swellings, leaf curls and yellowing Powdery Mildew.

The establishment of an economical system for the prediction and classification of plant leaf diseases is the objective of the proposed work. The primary aim is to create a specialized deep learning model devoted to predicting and detecting these diseases, surpassing the accuracy rates achieved by existing methods. This will be accomplished by training the model on a larger dataset and experimenting with different architectures. Furthermore, the goal is to reduce the training time by employing pre-trained models, all while maintaining a superior accuracy rate.

2. LITERATURESURVEY:

1. PLANT LEAF DISEASE DETECTION USING CNN AND RASPBERRY Pi G.Rama Mohan Reddy, Netcam Sai Sumanth, N. Sai Preet ham Kumar- This paper proposes the visualidentificationofplantdiseasesthroughnaked-eyeobservationbutacknowledgesitsinherentlimitations in accuracy. To improve precision, the utilization of SVM for prediction is introduced, achieving an accuracy rate of only 70% even with a well-constructed dataset. Consequently, the paper suggests the adoption of Raspberry Pi for disease identification. The methodology entails employing convolution neural networks (CNN) for image processing, capitalizing on their varied features to proficiently discern plant diseases. This approach holds significant value for research applications, as the CNN algorithm facilitates precise detection of leaf diseases.

2. LEAF DISEASE DETECTION USING RASPERRY PI LAYA YESUDAS1, SANTHIYA.S2 PARIMALA.R3, MOHAMMAD HARRISS-Green Plants plays a crucial role in the overall environment, serving as the foundation for the sustainability and long-term well-being of ecological systems. This paper introduces a system employing Raspberry Pi to distinguish between healthy and unhealthy plants, alerting farmers through email notifications. The implementation incorporates Tensor Flow tools for mathematical computations.

3. MONITORING OF HYDROPONICS SYSTEM USING IOT, NiveshPatil1, Shubham Patil1, Animesh Uttekar1, A. R. Suryawanshi2 14-Agriculture plays a crucial role in the advancement of rural nations worldwide. In India, approximately 68% of the population relies on farming, contributing to one-third of the national income. Ongoing challenges in agriculture have consistently impeded the nation's progress. To address these issues, adopting smart agricultural practices and modernizing traditional farming methods could offer a potential solution. Hence, the goal of this project is to implement an aquaculture system using IOT technologies, incorporating the use of Raspberry Pi.

4. PLANTDISEASEDETECTIONUSINGCNN&REMEDY,
Adnan Mushtaq Ali Karol1, Drushti Gulhane2, Tejal Chandiwade3- The suggested system aids in identifying plant diseases and offers remedies that can serve as a defensive mechanism against these ailments. The information obtained from the Internet is systematically organized, with distinct plantspeciesidentifiedandreclassifiedtoconstructawell-organizeddatabase.Subsequently,at test dataset is acquired, containing various plant diseases used to assess the accuracy and confidence level of the project.

5. HOW CONVOLUTIONAL NEURAL NETWORK DIAGNOSE PLANT DISEASE, Yosuke Toda1, 2 and Fumio Okura1,3 - Significant advancements have been achieved in leveraging deep learning, particularly convolution neural networks (CNNs), for the classification of various plant diseases. However, a limited number of studies have delved into the reasoning process, leaving it somewhat opaque as a black box. Unveiling the CNN to extract learned features in an interpretable framework not only ensures its reliability but also facilitates model validation and training datasetevaluationthroughhumanintervention.Inthisstudy,diverseneuron-wiseandlayer-wisevisualization techniques were employed with a CNN trained on a publicly available dataset of plant disease images. Our findings demonstrate that neural networks can effectively capture the colors and textures specific to individual diseases during the diagnostic process, akin to human decision-making.

6. PLANT DISEASE DETECTION AND GROWTH MONITORING USING IOT Anudeep Department of Computer science and Engineering, Satya bhama Institute of Science and Technology, Chennai In India, as universally acknowledged, agriculture plays a vital role in the development of

Rural communities and then at ion as a whole. Agriculture has been the lively hood for people for over century.

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3. METHODOLOGY:

Embarking on the intricate journey of image processing and computer vision, Convolution Neural Networks (CNNs) stand as a distinguished class of deep learning models. Tailored for the intricacies of visual tasks, they have us her edinane we rain image recognition, empowering computers to autonomously grasp and decipher patterns within images. Unraveling the essence of a CNN involves navigating through several pivotal steps. At the heart of this neural network lies the fundamental operation known as convolution, a transformative process that propels the network into the realm of perceptive. Convolution layers make use of learnable filters, or kernels, for the processing of input images or feature maps. These filters, often configured as small grids like 3x3 or5x5, have the input image traversed, with element-wise multiplications performed and the outcomes aggregated. This process leads to the creation of a feature map highlighting specific visual features such as edges, textures, and shapes. Following the convolution step, an activation function is applied element-wise to the feature map. The widely utilized activation function in CNNs is the Rectified Linear Unit (ReLU), which negates negative values while preserving positive values, introducing non-linearity to facilitate the learning of intricate data relationships. Subsequently, pooling layers come into play to reduce the spatial dimensions of feature maps while preserving crucial information. Common pooling techniques include max-pooling and average-pooling. For instance, max-pooling selects the maximum value in a local region (e.g., 2x2) of the feature map and discards other values. Pooling enhances the network's resilience to small translations or distortions in the input, ultimately reducing computational complexity. After a series of convolution and pooling layers, the network typically concludes with one or more fully connected layers. These densely connected layers play a pivotal role in the formulation of final predictions. In image classification tasks, high-level features extracted by preceding layers are amalgamated to predict class labels. A Soft Max activation function is frequently applied to the output of the fully connected layer, converting raw scores into class probabilities. The predicted class is then identified based on the highest probability.

The discrepancy between the predicted class probabilities and the actual class labels in the training data is quantified by the loss function. The objective throughout the training process is to minimize this loss, a task usually achieved through optimization algorithms like stochastic gradient descent (SGD) or its variations. The process of propagating the error backward through the network, known as back propagation, enables the fine-tuning of the model's weights and biases. The network's parameters are updated iteratively to minimize loss and enhance the model's accuracy. Training is undergone by the CNN on a substantial dataset consisting of labeled images, allowing it to develop the ability to recognize patterns and features crucial for the designated task, whether it be object recognition or image classification. The training data is conventionally divided into training and validation sets, facilitating the assessment of the model's performance on unseen data. Following training, proficiency in making predictions on novel, unseen images during inference is achieved by the CNN. In practical applications, adaptation of CNNs initially trained on extensive datasets like

Image Net for specific tasks is achieved by modifying the network's to players, a technique referred to as transfer learning. This approach proves highly advantageous, especially when the available training data for a particular task is limited. Essentially, a specialized deep learning model is formed as a Convolution Neural Network designed specifically for image processing and computer vision tasks. Empowered by fundamental operations such as convolution, activation, pooling, and fully connected layers, it excels in tasks like image recognition, object detection, and medical image analysis, among others.

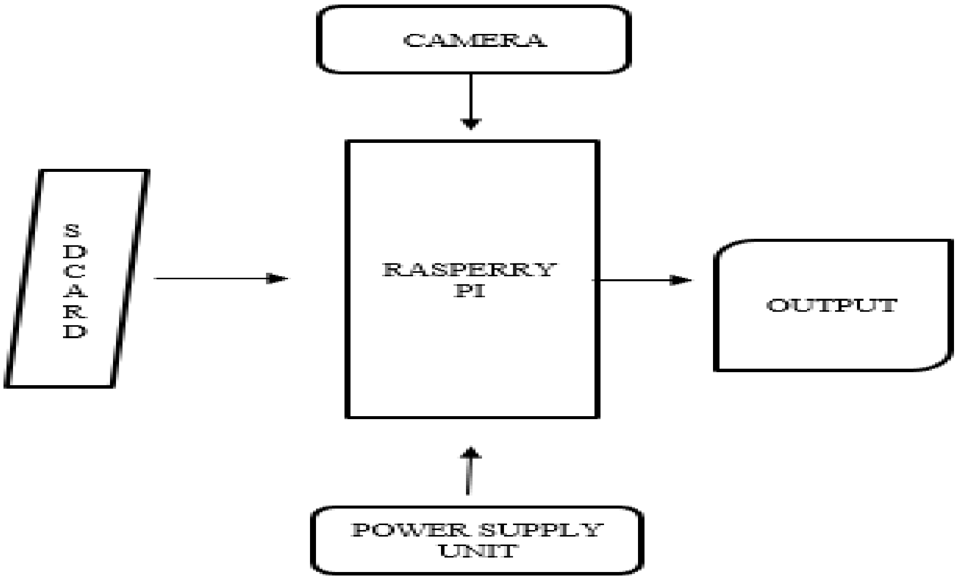

Fig.3.BlockdiagramforProposedModel

4. WORKING:

Deep learning has recently emerged as a crucial element in diverse fields like Medical Science and Plant Pathology, utilizing Convolution Neural Networks (CNNs). Networks trained on extensive datasets demonstrate increased accuracy compared to earlier methods. In this instance, model sunder went training using the Plant Village dataset, a publicly accessible compilation comprising 54, 306 images depicting 38 different healthy/diseased leaves across 14 plant species. The implementation of standardizing image dimensions to 224×224×3 and normalizing pixel values by dividing them by 255 was carried out to align them with the 18 initial model values. To tackle over fitting, the dataset was divided into training (70%), validation (20%), and testing (10%) sets, formatted as img.jpg to optimize the efficiency of deep learning processes. This methodological approach results in the enhancement of the speed and efficacy of deep learning with the provided datasets. The deep learning process is structured hierarchically, akin to machine learning, and is organized into tiers. Initial tiers specialize in learning specific features, and this acquired knowledge is subsequently transferred to the subsequent tiers. Initial tiers learn specific features, and this knowledge is then passed on to subsequent tiers. Each subsequent tier integrates and refines the information, constructing a progressively intricate hierarchy. Deep learning showcases its effectiveness in real-time applications, encompassing tasks such as object identification, language translation, and decision making. Its broad applicability extends to the scrutiny of extensive datasets, enabling predictions driven by knowledge. With its capacity to yield practical and immediate results, deep learning emerges as a formidable catalyst for pragmatic applications. The primary advantage of deep learning, in contrast to traditional machine learning, resides in its inherent

Ability to conduct automatic feature engineering. Deep learning autonomously delves into datasets to identify and integrate relevant features, expediting the learning process. Additionally, deep learning models exhibit versatility, adapting to a variety of datasets and effortlessly addressing emerging challenges in the future. Notably, deep learning plays a pivotal role in activities like generating captions for images and infusing color into black and white images. Transfer learning, a technique within the domain of machine learning, is particularly endorsed in the context of deep learning. Transfer learning emerges as a strategic methodology that involves leveraging pre- existing models as a foundational framework for computer vision tasks. This technique encompasses modifying a model initially designed for a specific task to better suit another related task. The adoption of transfer learning enhances efficiency by accelerating the progress of new tasks, aligning closely with multi-task learning, and addressing the concept drift phenomenon.

While not a discrete machine learning technique, transfer learning functions as a design approach within the broader landscape of machine learning. It stands out as a specialized discipline, particularly notable in deep learning, owing to the substantial resources needed for training intricate models on extensive and challenging datasets. The effectiveness of integrating transfer learning into the domain of deep learning relies on leveraging shared features acquired from initial tasks, facilitating their adaptation to related tasks—an aspect commonly known as inductive transfer. Attaining success in transfer learning within the realm of deep learning necessitates ensuring that the model's input dimensions align with those employed during the initial training. The visual depiction presented in Figure 2.6 provides a comprehensive overview of the process entailed in both training and testing when implementing transfer learning on a dataset. In the field of computer vision, the initial layers of neural networks play a crucial role in detecting image edges; the intermediate layers identify shapes, and the later layers capture specific features relevant to a variety of tasks. In the strategic execution of transfer learning, the emphasis is placed on capitalizing on the initial and intermediate layers while concurrently retraining the later layers. This approach effectively safeguards the labeled data from the task on which the model was originally trained. The primary objective of transfer learning is to distill valuable insights from prior tasks and apply them to tackle new challenges..

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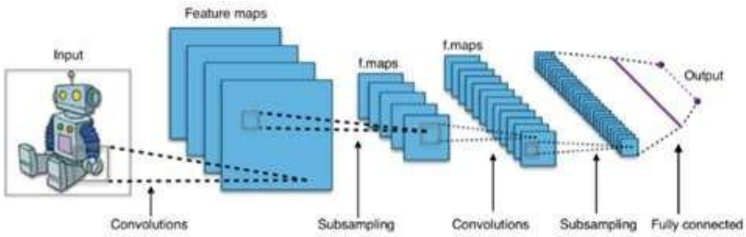

Fig4TypicalConvolutionalNeuralNetwork

Upon the completion of the Hardware Setup and Coding phase, the initiation of the process is carriedoutbypoweringontheMicrocontroller.Theimagecaptureprocedureiscommencedbythemicrocontroller, which is interfaced with a PC Camera. Subsequently, an in-depth analysis of the plant's health is conducted, potential diseases are identified, and corresponding disease names are presented, all through the invocation of the Convolutional Neural Network (CNN) Algorithm. The CNN application has been meticulously developed, making use of a dataset comprising over 1000instancesofboth healthy leaves and leaves afflicted with diseases .The training of the tens or stream is a time-intensive process, taking approximately 45 minutes, contingent upon the size of the dataset. The accuracy of disease detection exhibits a direct correlation with the dataset size, emphasizing the importance of a comprehensive dataset. Following the training process, the execution of the command for real-time leaf capture is facilitated through the Thing Speak Software in the terminal window .In real-time, images of the leaves are captured by the Raspberry Pi camera, and these images are compared with the previously provided dataset by the CNN algorithm. Results are generated based on the identified percentage of leaves affected by disease and those that are healthy. Precision in disease detection can be further optimized through dataset augmentation. After all preparatory steps have been completed; a conclusive precision assessment test is initiated by the script. The most accurate estimate of the trained model's performance on the classification task is yielded by this evaluation. A roster of identified leaves is produced in each execution, and subsequently, these values are transmitted to the Cloud. The results are then presented on the Web Server through the utilization of the Thing Speak Software.

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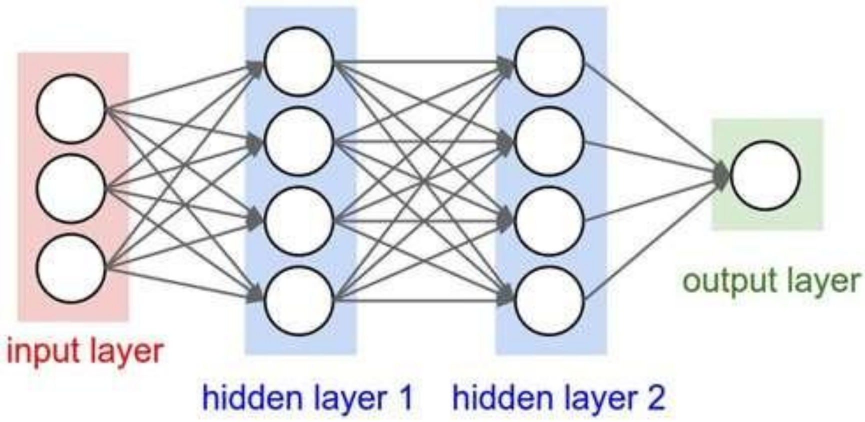

Fig5Simple DeepLearningNetwork

5. RESULTS:

The utilization of Convolutional Neural Networks (CNN) in the plant leaf disease detection project has yielded promising outcomes, marking a significant advancement in agricultural technology. The CNN model excels in identifying plant diseases by analyzing intricate leaf patterns, leveraging a dataset comprising over 1000 instances of both healthy and diseased leaves. This extensive dataset ensures the model's accuracy and robustness, matching the dataset's size. Tensor Flow served as the framework for training the CNN model, a process that efficiently completed within approximately 45minutes, highlighting its computational efficiency. The model's effectiveness was confirmed through conclusive evaluations, with results seamlessly displayed on a web server utilizing Thing Speak Software, facilitating accessible data interpretation.

Future enhancements in plant leaf disease detection will focus on leveraging advanced machine learning algorithms to further improve accuracy and efficiency. Integration of IOT technologies for real-time monitoring holds promise in automating surveillance and enabling prompt interventions.

Additionally, expanding data set sizes will enhance model training, ensuring its adaptability to diverse agricultural conditions and disease patterns. Automation and drone based surveillance represent pivotal areas for refinement, offering continuous monitoring capabilities across large agricultural expanses. Integration of real-time satellite imagery and drone technology can significantly bolster rearly disease detection efforts, allowing farmers to implement timely interventions and minimize crop losses effectively.

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In conclusion, the integration of CNNs into plant leaf disease detection systems marks a transformative step towards sustainable and efficient agriculture. Continued advancement sin technology promise to revolutionize disease management practices, fostering improved crop health and yield for agricultural communities worldwide.

Fig6InputOfProposedSystem

6. APPLICATIONSOFHPDDS:

6.1. Early Disease Detection in Hydroponic Systems:

Detecting diseases early in hydroponically grown plants is crucial as it can prevent wide spread contamination and significantly improve overall crop yield and quality. By identifying symptoms at their onset, growers can swiftly implement targeted treatment protocols, minimizing the spread of diseases and reducing crop losses.

6.2. Automated Monitoring and Alert System:

The implementation of a CNN-based system allows for continuous monitoring of plant health without the need for constant human oversight. This automated approach ensures that any signs of disease, such as discoloration or unusual growth patterns, are promptly detected. Real-time alerts can then be sent to farmers or growers via mobile devices or computer systems, enabling swift action to mitigate potential damage.

6.3. Precision Agriculture:

By integrating CNN technology, growers can achieve precise management of plant health parameters in hydroponic environments. This includes optimizing the use of essential resources such as water, nutrients, and pesticides based on the specific needs of diseased plants identified by the system. This targeted approach not only enhances crop productivity but also reduces unnecessary resource consumption, contributing to sustainable agricultural practices.

6.4. Remote Monitoring:

The ability to monitor hydroponic crops remotely through connected devices is facilitated by CNN-based systems. This feature allows farmers to access real-time data and monitor plant health metrics from any location, facilitating timely interventions even when physical presence is not feasible. Remote monitoring enhances operational efficiency and supports proactive management strategies.

6.5. Data-driven Decision Making:

CNN systems enable comprehensive data analysis over time, offering valuable insights into disease patterns and trends within hydroponic systems. By leveraging this data, farmers can make informed decisions regarding crop rotation, disease treatment plans, and preventive measures. This data-driven approach enhances agricultural productivity and resilience against diseases, optimizing overall farm management practices.

6.6. Integration with IOT (Internet of Things):

Integrating CNN-based disease detection systems with IOT platforms enhances automation capabilities in agriculture. This integration allows for automated adjustments of environmental parameters such as humidity, temperature, and light intensity based on real-time disease detection outcomes. Such adaptive control systems further stream line operations and improve resource efficiency in hydroponic farming.

6.7. Research and Development:

Researchers can utilize data collected by CNN-based systems to conduct in-depth studies on diseasedynamicsandmanagementstrategiesinhydroponicenvironments.Thisresearchcontributestoadvancements in plant pathology and informs the development of more effective disease prevention and control measures, benefiting agricultural communities globally.

6.8. Education and Training:

Educational institutions can leverage CNN technology to educate students and professionals about plant health monitoring, disease detection methodologies, and the practical application of advanced technologies in agricultural systems. This fosters skill development and prepares future agricultural professionals to leverage innovative solutions for sustainable food production.

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6.9. Enhanced Sustainability:

By reducing reliance on pesticides through targeted disease management, CNN-based systems promote sustainable agricultural practices in hydroponics. Minimizing chemical inputs not only mitigates environmental impact but also supports the production of healthier, pesticide-free crops, meeting consumer demand for sustainable food options.

6.10. Commercial Farming Applications:

Large-scale hydroponic farms stand to benefit significantly from the implementation of CNN-based disease detection systems. These technologies enhance disease monitoring and management practices, reducing production risks and ensuring consistent crop yields. By optimizing operational efficiency and minimizing losses, commercial growers can achieve sustainable growth and profitability in hydroponic agriculture.

In summary, a Smart Hydro phonic Plant Disease Detection System using CNNs represents a transformative innovation in precision agriculture. By addressing key challenges in disease management and resource optimization, these systems contribute to improved productivity, sustainability, and resilience in hydroponic farming practices.

7. SAMPLE OUTPUT

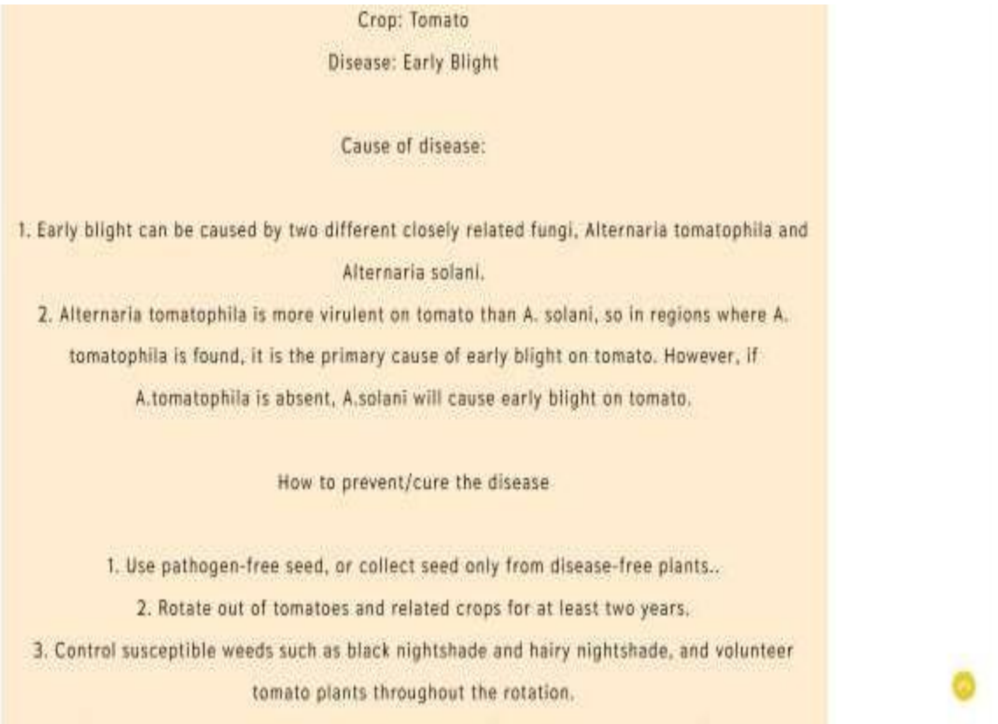

Fig6SampleOnputOfProposed System

8. CONCLUSION:

The implementation of Convolutional Neural Networks (CNNs) in a Smart Hydroponic Plant Disease Detection System represents a ground breaking advancement in precision agriculture. By facilitating early detection of diseases in hydroponically grown plants, optimizing resource managementthroughtargetedinterventions,andpromotingsustainablefarmingpractices,thistechnologysignificantlyenhancescropyield,quality,andoverallagriculturalresilience.Throughcontinuousmonitoringand data-drivendecision-making,growerscanefficientlymanageplanthealth,reducepesticide use, and mitigate risks, ensuring consistent production and environmental stewardship. This innovation underscores the transformative potential of CNNs in revolutionizing agricultural practices, paving the way for a more efficient, sustainable, and resilient food production system.

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