IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Review Of Deep Learning And IOT Based Crop Diseases Detection System

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ABSTRACT

Plant pest and disease management, especially in the early stages of infestation, is a critical challenge that poses significant threats and has potential to devastate agricultural crops, causing total yield loss and food insecurity. Traditional inspection methods are time-consuming and prone to errors due to limited labor expertise. Therefore, to tackle these challenges, harnessing advanced technologies such as artificial intelligence (AI), Machine Learning/Deep Learning (ML/DL), and Internet of Things (IoT) is essential for managing and mitigating agriculture hazards. This article presents a comprehensive review of the state-of-the-art DL architectures integrated with IoT-based systems applied to plant pest and disease detection (PPDD) by investigating different potential approaches that have been employed using DL and IoT up to the year 2024 to address challenges in agriculture. Convolutional Neural Network (CNN) architectures for image recognition, object detection, and their integration with IoT, embedded into mobile devices and unmanned aerial vehicles (UAV) are explored. Moreover, the research discusses the advantages and limitations of these techniques, emphasizing their architecture design, efficiency and accuracy. The findings demonstrate that there is a tradeoff between robustness and complexity among existing techniques, and authors recommend future trends aimed at creating robust models with fewer parameters that are more accurate and easily implementable on small IoT-based and portable devices suitable for in-field and real time applications. Furthermore, while existing review papers discuss either DL or IoT separately, this research paper uniquely focuses on their combined models, providing a comprehensive overview of the synergistic potential of leveraging IoT-driven technologies alongside advanced DL algorithms to ease the task of researchers in the field of precision agriculture particularly in PPDD.

KEYWORDS:- DL,CNN,PPDD,IOT.

1. Introduction

Since the mid-20th century, the global population has experienced rapid growth, increasing from approximately 2.5 billion in 1950 to 7.8 billion in 2020. It is projected to reach 8.5 billion by 2030, 9.7 billion by 2050, and 10.9 billion by 2100 [1]. The rapid growth of the global population implies a continuous increase in global food demand over the coming decades, placing greater demands on agricultural production [2]. However, crop pests and disease infestations have emerged as major constraints to improving both yield and quality. These threats not only cause direct reductions in crop productivity and quality but also pose a serious challenge to global food security. A study documented the impact of 137 pathogens and pests on five major staple crops across global hotspots, revealing that regions with rapid population growth and food shortages suffer the most severe agricultural losses [3]. The economic burden of crop pests and diseases is substantial, with an estimated 20% to 40% of global crop yields lost annually to pest infestations, translating to approximately $220 billion in economic losses worldwide [4]. With the intensification of climate change and the expansion of global trade, the geographical spread and frequency of pest and disease outbreaks are increasing, presenting an unprecedented challenge to global food security. Pests and diseases are a serious threat to crop diversity. The whitefly, a global polyphagous pest, severely impacts agricultural productivity, especially in solanaceous, cucurbitaceous, and leguminous plants [5] .

The agricultural business is today confronted with many challenges, including climate change, population increase, and resource limitations, which conventional farming practices are sometimes unable to meet. Technological solutions are required instead. AI-driven smart agriculture signifies an innovative approach in agri-tech, wherein artificial intelligence, machine learning, computer vision, and data analytics collaboratively establish a cohesive platform for contemporary farmers by unifying all activities within a singular environment. This article will examine the architectural design, technical elements, and practical applications of smart agriculture, focusing on its AI driven crop disease identification application, intelligent market.al.gorithms, and multilingual support features. The system's performance indicators, user adoption rates, and economic effects on participating farms will be assessed. Automated disease detection systems have transformed agriculture, providing accurate and prompt findings for both small- and large-scale farming. Deep learning and neural networks, especially Convolutional Neural Networks (CNNs), are integral to these technologies. Convolutional Neural Networks (CNNs) can discern between infected and healthy leaves using visual processing, facilitating early disease identification and control. This method improves agricultural output while maintaining crop quality. Precision farming, a cutting edge technique, utilizes sophisticated instruments to enhance crop productivity and refine farm management. It emphasizes aspects such as water, land stress, herbicides, and fertilizers, using image processing to assess agronomic difficulties with precision and efficiency [6].

ML-based applications for agriculture are still young, but are already showing promise. For instance, disease classification from images can be done using popular Convolutional Neural Network (CNN) architectures for different plants with different diseases [7]; relationships between weather data and pest occurrence can be retrieved using Long Short Term Memory(LSTM) networks for forecasting future pest attacks [8]; insect detection on leaves can be performed using object segmentation and deep learning techniques [9].

The IoT has revolutionized not just how we live our lives but also how we operate. The adoption of IoT is growing quickly across many industries, whether it be agricultural, safety, or healthcare [10]. IoT with robotics and artificial intelligence will increase the complexity of commercial farms while reducing manual workers from 90% to 10%. One of the world's major scientific efforts in agriculture is thought to be happening in India [11]. Agricultural growth has advanced as a result of numerous advancements in modern technology and creativity. Previous research has examined the application of contemporary methods in the agricultural industry, including IoT, sensors, cloud services, mobile computing, and big data analysis [12,13]. According to Ref. [14], a study on an IoT-based process in the context of agriculture, the outcomes were remarkable. The efficiency increased slightly, and what had previously been a human-intensive industry like agriculture has become more scientific [14]. Placed detectors around the fields, and the Raspberry PI (RPI) were utilized to manage them all. When a sensor and RPI are interfaced, leaf illness can be identified. Farmers are immediately informed of the condition of a field, such as plant diseases or crop-affecting factors like dryness, warmth, and wetness, via a WiFi host using RPI [15].

2. Literature Review

In recent years, researchers have explored various image processing and deep learning methods to detect crop pests and diseases effectively. Anand H. Kulkarni and Ashwin Patil R. K. in their work on “Applying Image Processing Technique to Detect Plant Diseases” proposed a method where images of plant leaves were captured using digital cameras and subjected to preprocessing techniques such as noise removal, image enhancement, and segmentation. The study aimed to automate early disease detection and reduce dependency on manual observation. However, due to limited dataset size and simple algorithms, the system showed low accuracy and struggled with complex disease patterns or overlapping symptoms[16]

R. Radha and S. Jeyalakshmi, in their research titled “An Effective Algorithm of Edges and Veins Detection in Leaf Images”, introduced an algorithm that detects leaf edges and veins to identify nutrient deficiencies and classify whether a leaf is healthy or diseased. The model utilized classification algorithms, integrating an RNN-based approach for improved detection. While this system provided a structured way to analyze leaf health, it faced issues with low classification accuracy and high computational load, which made it unsuitable for real-time IoT deployment in farms.[17]

M. V. Latte and Sushila Shidnal developed a system for “Multiple Nutrient Deficiency Detection” using the Canny edge detection method. This algorithm successfully identified edges and vein structures in leaves, allowing early detection of nutrient-related diseases. The primary advantage of this method was its ability to detect deficiencies before visible damage appeared. However, the model faced limitations in accurately distinguishing between different plant species and often required manual calibration to adjust to varying environmental lighting conditions.[18]

Pranjali B. Padol and Anjali A. Yadav worked on “SVM Classifier Based Grape Leaf Disease Detection”, where segmentation and image classification techniques were applied to detect and categorize grape leaf diseases. The use of Support Vector Machine (SVM) helped in achieving better classification results compared to basic image processing methods. The system proved useful in improving grape yield by providing early warnings of infections. Nevertheless, it still suffered from low accuracy when dealing with similar disease features and was not robust enough for large-scale or real-time applications.[19]

Ms. Chhaya Narvekar in her paper “Flower Classification Using CNN and Transfer Learning in CNN – Agriculture Perspective” utilized Deep Learning models such as MobileNet, VGG, and ResNet to classify different flower species. The study demonstrated the power of transfer learning in improving feature extraction and reducing the need for large datasets. The model achieved better generalization and higher accuracy compared to traditional methods. However, the challenge remained in handling high visual similarity between species, which sometimes led to misclassification. The study highlighted how CNN architectures could be extended to crop disease detection for better precision in agricultural monitoring.[20]

Sue Han Lee proposed a “Multi-Organ Plant Classification Based on Convolutional and Recurrent Neural Networks”, which presented a hybrid model combining CNNs and RNNs to process both organ-specific (leaf, stem, fruit) and generic plant data. The model, known as HGO-CNN (Hybrid

Generic Organ CNN), used a feature fusion approach to integrate spatial and temporal data, improving classification accuracy significantly. This research showed that combining multiple deep learning architectures could enhance model reliability in complex agricultural datasets. However, the system's high computational cost and complexity made it less suitable for IoT edge devices like Raspberry Pi without optimization.[21]

3. Related works

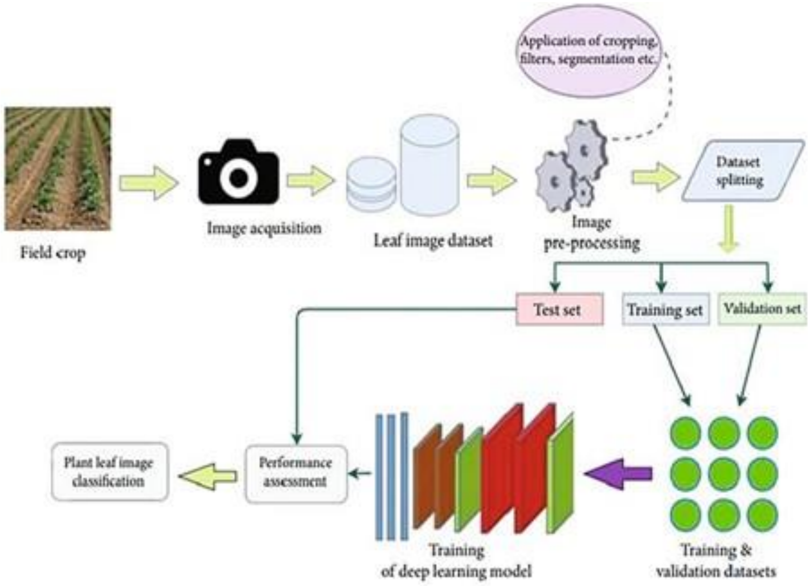
In this section, the previous scientific articles tackled the DL models that widely used for solving the problem of the plant diseases detection. While, other works discussed how to carry the advanced technologies "IoT" and techniques on the traditional central pivot for the plant diseases treatment. For plant diseases detection, a convolutional neural network model was presented for detecting and identifying plant leaf diseases based on visual data to boost accuracy, generality, and the overall efficiency of training. The experimental results showed that the proposed convolutional neural network-based model outperforms other previous models by a classification accuracy of 99.23%[22]. Sun et.al. [23], proposed a convolutional neural network architecture FL-EfficientNet (Focal loss EfficientNet), which was used for multi-category identification of plant disease images. The experiment used the public data set New Plant Diseases Dataset (NPDD) and compared it with three models: ResNet50, DenseNet169, and EfficientNet. The accuracy of FL-EfficientNet in identifying ten diseases of 5 kinds of crops is 99.72%.
In [24], R. Santhana Krishnan and E. Julie proposed an enhanced convolution neural network (CNN) based on a visual geometry group-16 (VGG-16) was used for potato leaf disease classification. The convolution layers of VGG-16 along with the Inception and the SE block were used in this research for classification. This model achieved the highest classification accuracy of 99.3%.
AI, and the IoT has advanced precision agriculture and precise plant health monitoring. The integration of these technologies enables real-time data collection, analysis, prediction, and informed decision-making to improve the accuracy and responsiveness of pest and disease management systems[25].

4. SYSTEM ARCHITECTURE

(a) AI AND ML COMPONENTS

Convolutional Neural Networks (CNN) for Disease Detection

AI-Enabled Smart Agriculture employs a complex image processing pipeline with powerful convolutional neural networks [26]. The design encompasses: a) Input Layer: Processes 224×224×3 RGB images b) Convolutional Layers: Multiple layers with 3×3 filters and ReLU activation c) Pooling Layers: Max pooling with 2×2 filters for feature extraction d) Fully Connected Layers: Dense layers leading to SoftMax classification e) Transfer Learning: Fine-tuned pre-trained models including EfficientNet-B3 and MobileNetV2The CNN architecture enables high-accuracy classification of 38 different crop diseases across 12 plant varieties, with performance metrics significantly exceeding conventional diagnostic methods.



Deep learning (DL) Techniques

The Convolutional Neural Network Technique Convolutional neural networks use deep feed-forward neural networks to examine multidimensional data. The CNN identifies channels that are activated after the classification of a certain feature at certain spatial coordinates [27]. The quantity of epochs used in the application of different convolution filters measuring 2 × 2 and 3 × 3 influences their precision. This is dependent on the size of the filter. Numerous pre trained architectures, such as VGG16, VGG19, ResNet50, ResNet152, InceptionV3, InceptionNet, and DenseNet121, are accessible for implementation using the CNN methodology [28].

Data Pre-Processing

Pre-processing data before feeding it to the model is common in most ML-based applications. Images are typically pre-processed using computer vision techniques to remove noise, to enhance the image contrast, to extract the regions of interest, to extract image features, etc. In general, image pre-processing steps usually lead to better model outcomes. The most common data pre-processing techniques are covered in the following sub-sections. [29]

Noise Reduction

Different types of filters, such as Gaussian and median filters, are used to reduce noise to obtain smoother images. These filters have an effect of blurring and removing non relevant details of an image, at the expense of potentially losing relevant textures or edges [30].

Images are usually stored in the RGB format, which is an additive color model of red, green, and blue components. Due to the high correlation between these color components, it is usually not suitable to perform color segmentation in the RGB color space. Therefore it is important to bear in mind that there are others color spaces such as HSV or L*a*b*. In HSVthe color components are: hue (pure color), saturation (shade or amount of grey), and value (brightness). In the L*a*b* color space, L* is the luminance (brightness), a* is the value along the red-green axis, and b* is the value along the

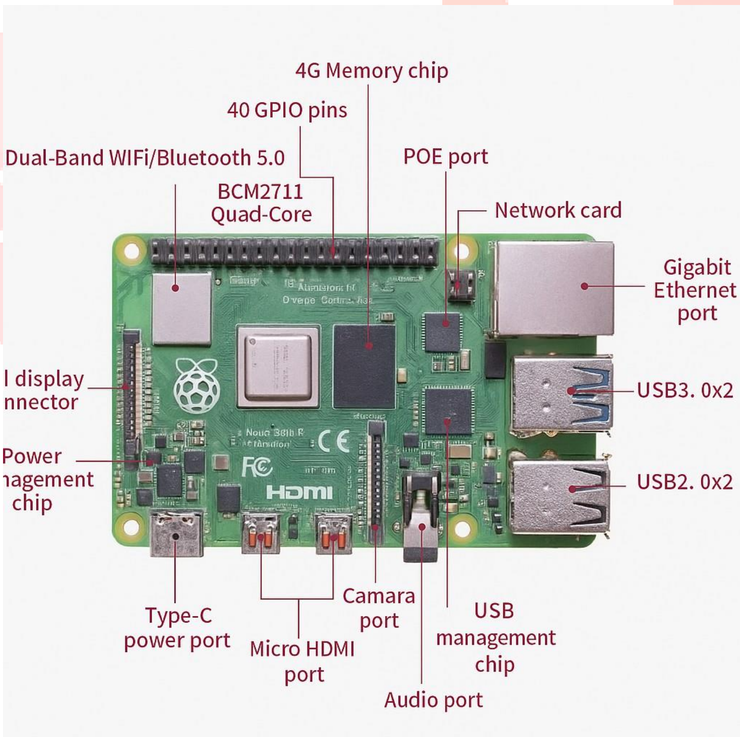
blue-yellow axis. In these color spaces, the brightness of a color is decoupled from its chromaticity, allowing the images to be processed with different lighting conditions [30].

(a) Black rot apple (original) (b) Black rot apple (grey)

PROCESSING DEVICE:

RASPBERRY Pi 5 The System on Chip (SoC) based device such as Rasp berry Pi 5 serves as the edge computing device onboard the UAV [31]. It processes the data collected from the high-definition camera using DL/CNNmodelstodetect pests and diseases in real-time. The Raspberry Pi 5 is suitable for edge computing due to its compact size and lightweight model, processing power that support complex and powerful DLmodelsas well as energy efficiency capacity, that make it ideal for integration into an IoT ecosystem [32].

The DL models based on CNN architecture such as Efficient Net, MobileNet and Inception series are mostly used due to their high efficiency, balancing accuracy and computational efficiency, makingthemidealfordeploymentonedgedevices like the Raspberry Pi 5 [33]

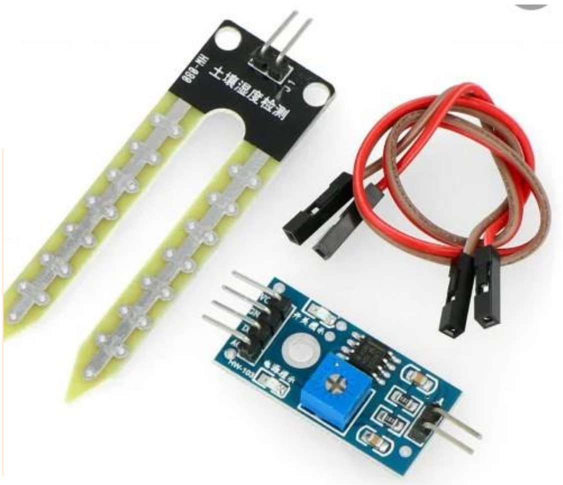


DATA STORAGE

The raw and processed data, including images of infected and healthy plants and their locations, is stored locally on the edge device or transferred to external storage devices. This data can be used for further analysis or historical record-keeping. A128GBmicroSDcardarecommonlyusedforlocalstorage, ensuring that sufficient data can be retained even during long missions[34].

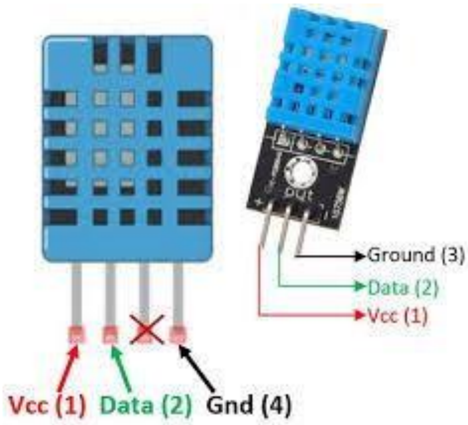
Monitoring of Soil Moisture and Water Levels

Soil monitoring has developed into one of the most challenging agricultural areas, both for manufacturers and farmers. Numerous environmental issues associated with soil monitoring affect agricultural yield. When these sorts of obstacles are correctly identified, farming patterns and methods become readily understandable. The soil's moisture content, wetness, fertilizer application, and temperature trends are all being monitored. Soil's moisture environment management system uses soil humidity and moisture sensors. By proposing an appropriate fertilizer approach, the results of a soil monitoring test report assist farmers in increasing crop yield [35]. The sensor can read both analog and digital outputs. The judgment is made based on data collected from sensors and compared to predefined threshold levels. The soil moisture sensor is used to regulate the irrigation system's automatic operation. When the moisture level goes below the threshold value, the water pump is triggered [36].



Temperature and humidity sensor:

The temperature and humidity sensor used here is DHT11 which is used to measure the surrounding air, and a capacitive humidity sensor and thermistor in DHT11 spits out a digital signal on the data pin. It also has a resistive elements and a temperature measuring devices. Its technology is highly reliable and more stable. [37]



Conclusion

Crop diseases cause large financial losses for the agriculture sector and pose a serious danger to the world's food security. This piece offers a web-based crop disease detection system that uses

sophisticated picture processing and environmental data to give accurate diagnosis and treatment.
An important development in agricultural operations is AI-driven smart agriculture, which shows how AI combined with computer vision and machine learning can revolutionize traditional farming methods. The system may effectively address important modern agricultural issues like disease detection, market efficiency, and information dissemination, according to the system's performance indicators.
The accuracy of disease diagnosis has increased thanks to the use of machine learning methods like convolutional neural networks (CNN) and libraries like TensorFlow. Additionally, cutting-edge models of artificial intelligence,

- The proposed system combines IoT, Deep Learning, and automation to deliver a holistic solution for crop pest and disease management. Unlike traditional systems that only detect problems, this project introduces laser-based pest elimination and automated irrigation, ensuring both crop protection and resource optimization. By integrating soil moisture, temperature, and humidity sensors, the system provides comprehensive monitoring of plant health and environmental conditions.

- This intelligent framework reduces dependency on manual inspection and harmful pesticides, while empowering farmers with real-time alerts and actionable insights. The outcome is a sustainable, eco-friendly, and scalable precision agriculture solution that can significantly reduce crop losses, conserve natural resources, and contribute to global food security.

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